Essays in Applied Labour Economics

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presented by

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Essay 1: A New Approach to Evaluating Active Labour Market Programs

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Essay 1

A New Approach to Evaluating Active Labour Market Programs

Joint with Rafael Lalive and Josef Zweimüller

Abstract
This paper calculates the impact of Active Labour Market Programmes through the use of three new indicators measuring the application performance of the unemployed. These indicators can be measured repeatedly and therefore allow the usage of Panel Regression methods, cancelling out any unobserved individual heterogeneity. To implement the new approach, data on 30,000 applications has been collected. Using this data, a large positive effect for unemployed with a long term unemployment forecast was estimated. For unemployed without such a forecast, the effect is much smaller. The paper also shows that the new evaluation approach fulfils the requirements of a good controlling instrument: It is accurate, detailed, non-intrusive, inexpensive and therefore easy to keep up to date, easy to understand and communicate.

1. Introduction

Many national labour agencies use a large proportion of their resources for Active Labour Market Programmes (ALMPs), with the intention to make the reintegration of unemployed persons quicker and longer lasting. In 2007, the average OECD member country spent 0.56 of its GDP on ALMPs. In order to improve the quality of these expensive programs, a good controlling instrument is needed. This controlling instrument should estimate the ALMP effects in an unbiased way. It should be easy to understand and communicate and therefore being trusted. It should be detailed so that its findings can be used to identify which ALMP is successful for which group of unemployed. Ideally, the instrument would indicate why an ALMP is successful or unsuccessful, so existing programs can be adapted. It should be relatively cheap so it can be applied on a regular basis, to keep the results updated and relevant for the current labour market.

Unfortunately, such an instrument doesn't exist yet. In some ways this is not surprising, as the challenges are nontrivial: A direct comparison between participants and non-participants of a certain ALMP is not possible, as it is very likely that characteristics which influence the decision of participation (by the unemployed or case worker) also influence the outcome on the labour market. Comparing only very similar participants and non-participants as done through the intensively used matching approach has limits because it can only rely on the characteristics recorded in databases. Often, many important features and skills of the unemployed are missing in these records.

This study tries another attempt at the old research question; how can one measure the effect of an ALMP accurately? It doesn't do this by applying more sophisticated statistical tools, but instead through a different approach and different data. As part of this study, a nine months data collection period was carried out at an agency of the Swiss unemployment insurance in the city of Zurich. During this time, all applications written by the unemployed at this agency, their characteristics and outcome were documented. A sample of 30,000 applications was then coded and recorded electronically. Further data on the unemployed and the ALMP was collected through surveys among the case workers and the persons responsible for the ALMP. Through this, a very rich dataset was assembled.

Based on the idea of Falk, Lalive and Zweimüller (2005), this paper measures changes in the application process of the same person rather than comparing different individuals. It does this by measuring the probability of a job interview and the frequencies of applications and interviews per week, indicators which can be repeatedly observed. While Falk et al. applied an experimental design (by adding ALMP diplomas to randomly chosen applications, comparing the impact of the diploma on the success rate) this new approach measures the impact on a purely observational base, comparing applications before, during and after ALMPs.

The method of comparing the success of applications has been frequently used in the discrimination literature (under the name of correspondence-testing), but is new for the ALMP evaluation literature. The approach has great advantages over traditional evaluation methods: It allows cancelling out all time-invariant characteristics of an individual by using quite simple statistical tools. It permits the calculation of individual treatment effects. It is non-intrusive and since it does not need the consent of the persons involved, doesn't result in a selection bias. Because the whole spell from beginning to end can be observed, all the different effects proposed by theory can be identified. Further, it fulfils the controlling criteria mentioned above (unbiased, easy to understand and communicate and therefore trusted, detailed, inexpensive and easy to update). This makes it a very powerful controlling tool.

Using the data collected at the trial agency, the following results were calculated through panel regression estimation with fixed effects: Overall, the ALMPs had a large positive effect on the participants. Participation resulted in more interviews per week (the number is increased by 0.0308, which, at the time the average ALMP is announced, is equivalent to an 11.1 % increase), a higher probability of a job interview (plus 0.0107, which is equivalent to a 9.4 % increase) and a higher number of applications per week (plus 0.0972 or 3.9 %).

The effects are particularly large for unemployed with a long term unemployment forecast while they are quite small for unemployed with a forecast below twelve months. This difference seems to hold important information on who should be sent to participate in ALMPs: It is mainly the unemployed with low chances of a quick reintegration into the labour market who gain from the programs.

The results show further that the different subtypes of ALMPs fare very differently: On average, basic courses, the category "other courses" (a mix of IT and vocational training) and basic qualifications do well. Employment programmes and personality oriented courses on the other hand have a negative effect. Programs with negative effects don't have to be abolished altogether; but either the programs or the mix of unemployed participating have to be adapted in order to reap the benefits.

The paper is structured in the following way: In section 2, the four effects proposed by theory are illustrated and a short overview on the literature is given. The advantages of the new approach are elaborated in further details in section 3, and the data used is described in section 4. Section 5 describes the three application indicators and their development over the duration of the unemployment spell. In section 6 the ALMP effect is measured through Panel Regression analysis. The main models are presented and several sensitivity tests conducted. Section 7 looks at the distribution of the effect, to find out under what circumstances the ALMP result in a positive effect. Section 9 explains why the method is a good controlling method despite its inability to track the application process to its ultimate goal, the job, and Section 10 concludes.

2. Theory and related literature

The success of ALMPs has created great interest over the past two decades and as it is connected to the wider topic of evaluating welfare programs in general, the related literature is vast. A good overview over the literature, methods and challenges involved can be gathered from Heckman et al. 1999, Smith and Todd 2005 and a recent study by van den Berg et al. 2009.

There are four main effects proposed by the evaluation literature: the threat effect, the lock-in effect, the skill enhancement effect and the signal effect. These effects occur at different times during the unemployment spell, as illustrated by Figure 1, and have different effects on the three application indicators used in this study. The first one of these three indicators is “interviews per week”. This is the indicator which policy makers are most interested in, because it captures both quality and quantity of the application process and is closely connected to the final outcome, a new job (for how close exactly, see section 9). It is a vector of the two other indicators: “interview probability” and “applications per week”. Interview probability captures the chances of the application resulting in a job interview. It could be interpreted as the qualitative side of the application process. It is to a large extent determined by the employer who chooses the requirements and the number of applicants to the job opening (through his or her use of advertising). Application frequency, measured in applications per week, on the other hand can be interpreted as the search intensity, or the quantitative side. It is directly influenced by the unemployed person his or herself (and the unemployment agency, which sets a minimum requirement).

The first effect, the threat effect, starts right after the unemployed has been informed about her or his participation in an ALMP (for an overview on the threat effect, see Rosholm and Svarer 2008). This effect caught a lot of attention in research, especially after the paper of Black et al. 2003 which concluded that the threat effect is the driving forces behind the evaluated welfare program in Kentucky. It predicts that the search intensity rises after the announcement, as the unemployed is not keen on joining the ALMP. What happens to the interview probability is unclear and depends on how dry the pool of suitable jobs is. If suitable jobs are abundant, the probability should stay the same (maybe even rise because of better applications being written), if not, the probability falls as each further application is a worse job match than the one before. Because the probability of these additional applications is unlikely to be zero, one would expect the effect on interviews per week to be positive.

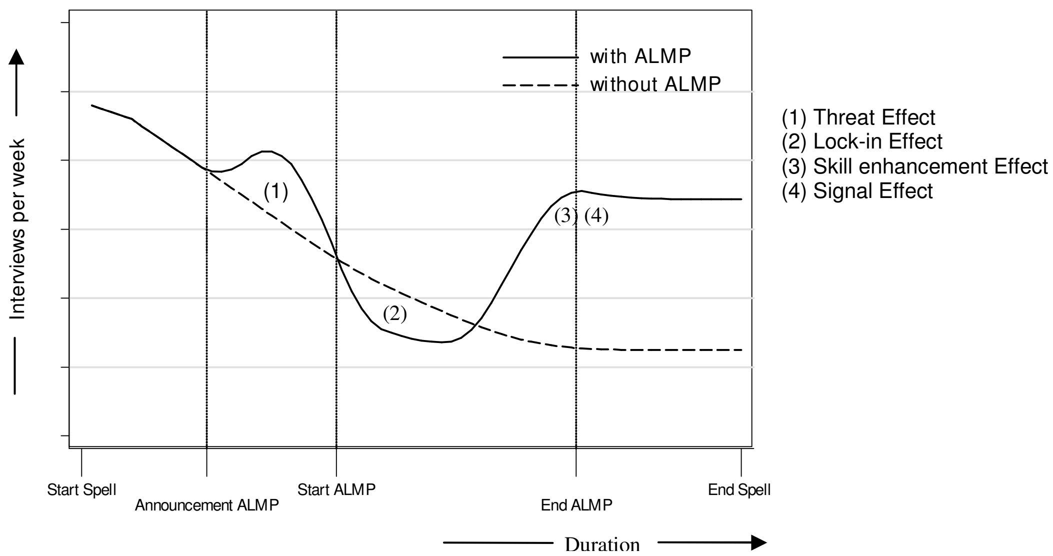

Figure 1: The four ALMP effects proposed by theory

After the ALMP has started, theory predicts the occurrence of a second effect, the lock-in-effect. This effect happens if the ALMP is demanding and doesn't leave the unemployed enough time to write as many applications as they did before the ALMP started. This will decrease the number of applications a person writes per week. Because unemployed persons are probably inclined to stop writing the applications for jobs they think they have a low chance to get, the average application probability should increase. Overall however the effect results in a lower number of invitations to job interviews. A different explanation of the lock-in effect is that an unemployed person reduces the search efforts if the program is attractive and positive treatment effects are anticipated (Carling and Richardson 2004). Finally, the lock-in effect could result if the case worker of the unemployed person reduces counselling efforts while the unemployed is participating in an ALMP (Ragni 2007). All three explanations point to lower search intensity during the ALMP.

Increasingly with the advancement of the ALMP, and especially once the ALMP has finished, the desired effects should set in, i.e. the skill enhancement and/or the signal effect. The two differ in as far the skill enhancement is an effect on the know-how of the unemployed, like better application techniques and improved language skills. The signal effect on the other hand unfolds when the unemployed is in a better position to reveal information (a signal) to a potential employer about her or his productivity (Carling and Richardson 2004). One would expect an increase of chances on the labour market through this signal, but the diploma can backfire if it actually signals a lack of knowledge (Falk, Lalive and Zweimüller 2005).

Table 1 summarizes the different effects. It also shows the overall trends in the three application indicators as predicted by theory. The overall trend for the probability of a job interview is downward: employers get more suspicious as they interpret a long duration of unemployment as a signal for low employability, low productivity or low work moral (Rosholm and Svarer 2004). As for applications per week, one would expect this indicator to rise over time as unemployed become more desperate with the end of the entitlement period nearing, opening up their search field and writing more applications. The trend for interviews per week is driven through the other two indicators, and given that the interview probability presumably falls steeply at the beginning and then flattens out, and the number of applications per week increases gradually at the beginning, but then gains momentum later in the unemployment spell, one would expect interviews per week to fall quite quickly at the beginning, flattening out and then increasing towards the end.

	Overall Trend	**Threat effect** (after announcement)	**Lock-in Effect** (during ALMP)	**Skill enhancement Effect** (after ALMP)	**Signal Effect** (after ALMP)
Interviews per week	- (steep fall at beginning, flattening and increase towards the end)	+	-	+	+ / -
Probability of a job interview	- (steep fall at beginning, later flattening)	-	+	+ (dominant indicator)	+ / - (dominant indicator)
Applications per week	+ (slow increase at beginning, later gaining momentum	+ (dominant indicator)	- (dominant indicator)	0	0

Table 1: The influence of the four effects on the application indicators, as proposed by theory

Note: "+" indicates an increase, "-" a decrease and "0" no changes in the indicator through the effect

It is important to note at this point that these are all effects measured on a short term basis (rather than long term effects on salary, job satisfaction etc.) and on the individual level. A possible substitution effect (another worker is displaced because the unemployed finds a job, so the net gain in employment is zero) can only be measured on the macro level. There are also effects on the non-participants (threat effect through the pure existence of ALMPs) and even on employed workers (higher tax burden as ALMPs have to be paid for). There are limits to the microeconomic analysis. In terms of learning which ALMPs work and why, and to develop a controlling instrument, the micro approach seems to be the way forward however as macroeconomic analysis can estimate the effect only on a very aggregate level.

There have been several studies on Swiss ALMPs since they've been introduced in the late nineties. Lalive et al. (2000), accounting for participation selectivity using a multivariate duration model, estimate that during an ALMP, participants have a lower exit rate through the lock-in effect. Once the ALMP is finished, the authors find a strong positive effect for women, but none for men. Gerfin and Lechner (2002), using the matching approach, found that wage subsidies work well, but conclude that vocational training programmes show disappointing performance. A study of Lechner and Smith (2007) concludes that the current allocation of unemployed to ALMP by case workers is inefficient and that efficiency is as low as if a random rule would be used. In a recent study, Lalive et al. (2008) used both "timing-of-events" and matching estimation. While the estimation based on "timing-of-events" showed that none of the Swiss ALMPs shortened unemployment duration, the matching results were similar to those of Gerfin and Lechner, concluding that wage subsidies show good results while training and employment programmes do not. In a macroeconomic study, Zweimüller et al. (2006) estimated that the positive effect of wage subsidies has a darker side: a very small negative effect on all non-participants actually results in a negative overall effect for the whole economy. Employment programmes on the other hand have a negative impact on the participants. Through their deterring effect however, they have a small positive impact on all non-participants, which results in an overall positive effect. For many of the ALMPs used in Switzerland therefore, the calculated results are mixed at best. They seem to work well for certain groups, but in average fare quite poorly. This weak performance doesn't seem due to an especially bad provision of ALMPs in Switzerland, but rather reflects what researchers have found all over the world.

3. The new approach and its methodological advantages

While many statistical approaches have been used over the years, they all had to come to terms with the fact that, with the existing data, very sophisticated methods had to be applied, many of those relying on strong assumptions. Heckman et al. (1999) pointed out that "the best solution to the evaluation problem lies in improving the quality of the data on which evaluations are conducted and not in the development of formal econometric methods to circumvent inadequate data." The innovation of the new approach being applied in this study is indeed not the statistical method but new indicators, possible through a unique data set especially collected for this study.

The idea of the new approach is based on the work of Falk, Lalive and Zweimüller (2005). These authors introduced a new indicator into the ALMP evaluation literature; the probability of a job interview. Falk et al. (2005) recruited ten unemployed persons and got them to write 20 applications each. While the quality of the applications was held constant, a diploma of an IT training course attended by the applicant was attached to 10 randomly chosen applications of each unemployed. The outcome of the application (did the application lead to a job interview?) was then reported back by the unemployed to the authors. The focus of the paper was on the signal effect of the IT courses: how well is a course received by potential employers? The study produced interesting results: while on average adding the diploma had a negative (not significant) effect, the individual effects spread from positive to negative. Adding the IT-diploma was clearly disadvantageous when applying for jobs which required good IT skills. The fact that someone had to attend an IT course organized by the unemployment insurance was taken as a signal for low IT knowledge.

The approach used by Falk et al. is related to the "correspondence testing" method which is commonly applied in discrimination research: Two fictional applications are sent out which differ only in the gender or nationality of the applicant, and the researcher compares the success of both applications. A good overview over correspondence testing is given by Bertrand and Mullainathan 2004 who used the approach using African-American and white American-sounding names to test for discrimination. The method has been used by Oberholzer-Gee 2008 using applications from unemployed and employed to test for an unemployment stigma. In recent papers, Carlsson and Rooth (2007) measured the effect of different ethnic backgrounds and Drydakis (2009) the effect of the gender of the applicant on the application success.

While common in the discrimination literature, the approach has not been used in the ALMP research. However, the ALMP effect can be analysed by using the probability of a job interview as indicator, measuring how employers “discriminate” between ALMP participant and non-participants. This new indicator has a tremendous advantage over other indicators used so far in studies, e.g. duration, number of months unemployed in the next year and salary in the new job, which lies within the fact that it can be measured several times over the duration of unemployment instead of only once. This makes it possible to calculate an effect not just by comparing two persons, but by comparing the same person over time. Thus unobserved heterogeneity between persons which is time-invariant can be completely eliminated.

Furthermore, the new indicator allows the calculation of individual treatment effects instead of average treatment effects over all participants or groups of participants. This enables the researcher to observe the distribution of the effects among individuals participating, and simplifies identifying groups of individuals who benefit from the ALMPs (Falk, Lalive and Zweimüller 2005). Because the new approach conducts its estimation without a control group, another issue can be avoided: Sianesi 2004 argues that, depending on the program, all unemployed persons will join an ALMP, if only the duration of the spell is long enough. If the reason that the person doesn’t participate in an ALMP is that she or he found a job before the ALMP could have been announced, this could lead to a distortion of the estimation not in favour of the ALMPs.

The idea of Falk, Lalive and Zweimüller (2005) is used for this study again, but modified in two main aspects. In addition to the indicator “probability of a job interview”, two additional indicators are used: the number of applications per week and interviews per week. A second difference is that instead of the experimental design, a purely observational design is implemented. While such an observational approach allows less control over the application process (the quality of the application cannot be held constant, for example), it has several advantages: It is not as time consuming and allows therefore collecting data on a much higher number of observations. It is non-intrusive because it doesn’t change the application process; the data represent the “normal” behaviour outside the monitoring period. The consent of the unemployed isn’t necessary to collect the data as in Switzerland; it is already standard that some data on applications is collected by the case workers. This is an advantage because no special incentives to participate in the data collection have to be created and therefore potential distortions can be avoided. In contrast to the way correspondence testing is usually used, no fictional applications have to be created; this has the advantage that applications are as real as possible. Forging applications can be difficult for researchers if applications from a whole range of educational and occupational backgrounds have to be mimicked. And because the whole unemployment spell from beginning to end can be observed, all effects proposed by theory can be identified and measured, not just the signal effect. All those characteristics make it possible to create a powerful controlling instrument which fulfils all the criteria mentioned in the introduction (unbiased, easy to understand and communicate and therefore trusted, detailed, inexpensive and easy to update).

4. Data

Data on the application process is systematically gathered in all Swiss unemployment insurance agencies, using a self-reporting sheet filled out by the unemployed person. The unemployed track all their applications over the course of a month and hand the sheet over to the case worker at the end of the month. Most of these forms are filled out by hand, and while they are archived for quality checks and lawsuits, the information isn't stored electronically. The data has not been used for research so far.

In order to make this data source accessible and by this enabling the new form of evaluation, the data on the application sheets has to be stored electronically. This has been done as a trial run in a single agency of the Swiss unemployment insurance, the Zurich-Staffelstrasse agency. Being a medium sized agency with both clients from city and rural areas and with a wide variety of occupations, this agency seemed well suited. Data on 30,000 applications was gathered between 1st of July 2007 and 31st of March 2008.

For efficiency reason, a stratified sample of the persons registered during the observational period was taken: The sample contains all unemployment spells with at least one ALMP participation (a quarter of all unemployed registered at Zurich-Staffelstrasse) and a random selection of a third of the spells in which the unemployed did not attend an ALMP. This sample led to a database containing data of 806 unemployment spells. Applications within the lay-off period and applications during the last month of unemployment were dropped, as these periods are subject to different rules by the unemployment insurance. Including them would distort the analysis. Spells which consisted solely of applications of the above mentioned kind were dropped with them.

This leaves 738 observed spells, 338 of which are treated spells (unemployed participated at some stage of the unemployment spell in one or several ALMPs), containing a total of 17,910 applications. The 400 untreated spells (unemployed didn't participate in an ALMP at any time of the spell) include 12,081 applications. The number of observations decreases steeply as the duration of the spell increases; more and more unemployed leave as they find a job. As shown in Figure 2, over the first few weeks of unemployment the majority of applications stem from unemployed who will not participate in an ALMP during their spell. As time passes on, an increasing amount of the data comes from persons with ALMP. The case number can be low when looking at the later stages of the unemployment spell (that explains some of the high fluctuation in Figure 3 to 5).

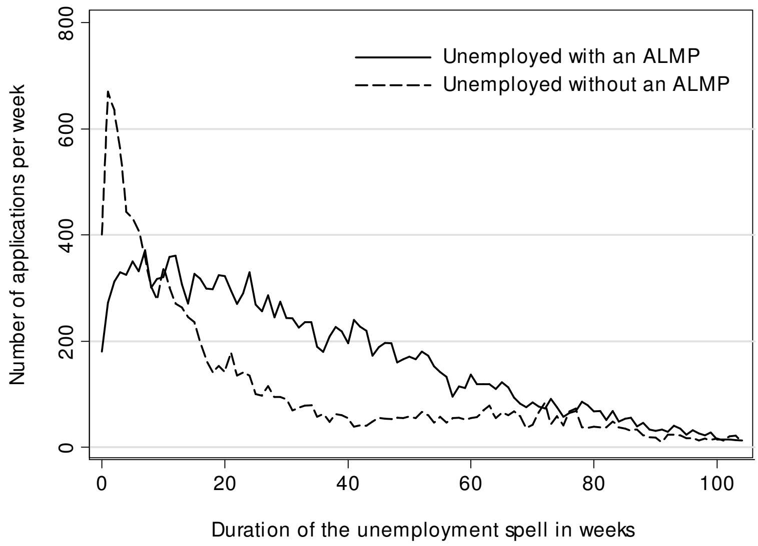

Figure 2: Number of observations recorded in the dataset, per week of the spell

Note: The graph shows the number of applications recorded in each of the weeks of the spell. The duration is plotted until the 104th week, after which the entitlement time frame expires. A total number of 738 unemployment spells are observed, 338 of which contain an ALMP participation at some stage of the spell ("unemployed with an ALMP").

Two objections to the data quality could be raised, both in connection to the self-reporting nature of the application sheets. The first possible objection could be that not all records are truthful and that some unemployed record applications they have never written. While wrongly recorded data (on purpose or by mistake) cannot be ruled out, the amount of purposeful cheating should be rather small, as case workers regularly check back with employers if the unemployed have indeed applied to the job indicated on their self-reporting sheet. Even if a small amount of cheating remains, this could only distort the calculation if more or less cheating is going on after the ALMP has started. There is nothing pointing to such an effect. The second objection could be that because of the requirement to write at least 8 to 12 applications, many unemployed don't bother writing all their applications down and instead stop once the minimum has been reached, therefore depriving the dataset of all their other applications. Again, this doesn't seem to be the case, neither according to statements by the case workers, nor showing up in the data. The applications are more or less evenly distributed over the stretch of a month, especially when looking at unemployed with ALMP (see Annex 1). If only the first 10 or so applications would be recorded, you'd expect an accumulation at the beginning of the month.

There is one more issue which has to be addressed in connection to the reporting sheet: Among other entries, the unemployed record the outcome of the application, whether they had an interview, a job offer or a rejection. The case workers at the trial agency reported that there was some confusion about the meaning of "job interview" when unemployed were carrying out personal applications (showing up at a company's door step and asking for a job). Some unemployed recorded such a personal application as an interview, others didn't. A sensitivity test in section 6 checks if the results change if applications from unemployed who reported almost all of their personal applications to be successful are left away. If not otherwise mentioned, all applications are used.

Apart from the self-reporting application sheets, data sources used include the electronically registered data of the unemployment insurance on the unemployed persons, a survey conducted among the case workers at Zurich Staffelstrasse (gathering additional data on the unemployed, e.g. a forecast regarding the unemployment duration of each person and the motivation to participate in the ALMP) and a survey among the employees responsible for the organization of ALMPs at the Office for Economy and Labour of the canton of Zurich (gathering diverse data on the ALMPs).

5. Changes in the three application indicators over time

To get an overview, the three application indicators are plotted over the duration of the unemployment spell. The duration is plotted until the 104th week, after which the entitlement time frame in Switzerland expires. Most unemployed use their benefits up beforehand, usually in the 18th month. There are several deviations from this pattern for persons who haven't paid into the unemployment insurance (shorter benefit period), elderly (longer period) and persons who participate in a work subsidy scheme (longer period).

The changes in the **number of interviews per week** over time are shown in Figure 3. The similarity between the two groups is striking: For the first 10 weeks the number of interviews per week is exactly the same. For the remainder of the spell the development seems similar for both groups, with the unemployed without an ALMP showing higher volatility and a slightly higher level. This indicator can be considered a result of both other indicators. Its downward trend however, as the next two graphs show, clearly stems from the decreasing probability of a job interview over time, while the gently raising number of applications per week does little to offset this downward trend.

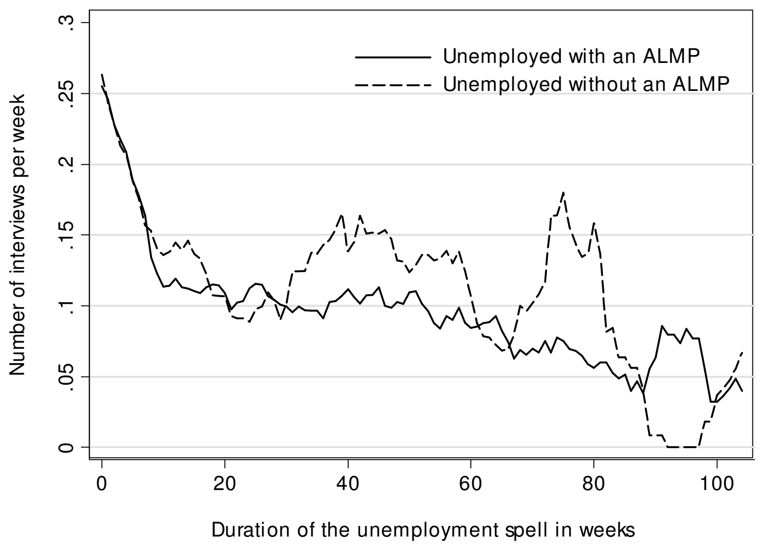

Figure 3: Frequency of interviews

Note: The graph shows the average number of interviews per week, giving equal weight to each unemployed registered in a certain week. The duration is plotted until the 104th week, after which the entitlement time frame expires. A total number of 738 unemployment spells are observed, 338 of which contain an ALMP participation at some stage of the spell ("unemployed with an ALMP"). Because of low observational numbers in certain weeks, a nine week moving average is used.

Looking at the development of the second indicator, **probability of a job interview** (Figure 4), one notices that both groups start off with similar chances: one in ten applications are successful. The similarity of that starting level, and in fact the whole development over time, is again surprising. One would expect quite stark differences between the two groups: Case workers send the persons with bad chances to an ALMP, and let the others search without training.

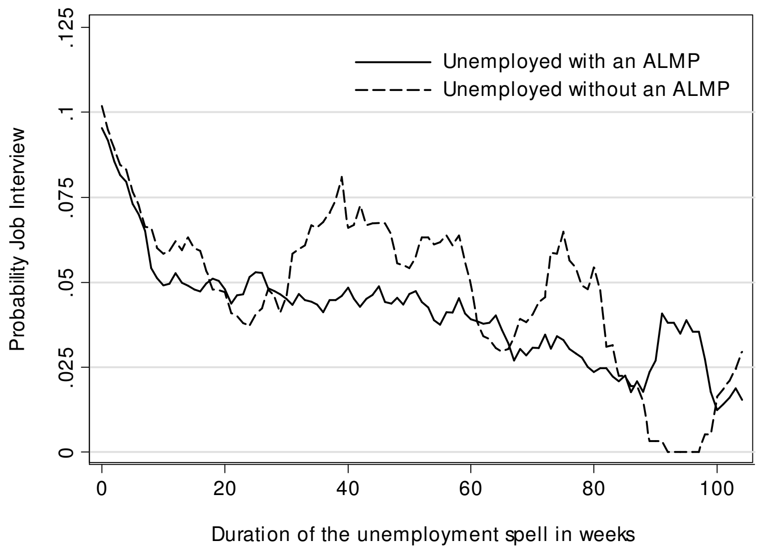

Figure 4: Probability of a job interview

Note: The graph shows the average probability of a job interview, giving equal weight to each unemployed registered in a certain week. The duration is plotted until the 104th week, after which the entitlement time frame expires. A total number of 738 unemployment spells are observed, 338 of which contain an ALMP participation at some stage of the spell ("unemployed with an ALMP"). Because of low observational numbers in certain weeks, a nine week moving average is used.

Chances drop for both groups quickly over time. This is what theory predicts: Employers get more wary as time progresses, taking the long unemployment duration as a signal for low employability. Unemployed themselves might broaden their search field which could entail a fall in the proportion of successful hits. Just as important though are the changes in the group composition: the successful unemployed leave early and the remaining ones have a lower average chance.

For unemployed with ALMP there seems to be a stabilization of the interview probability after the first six month of unemployment, before the indicator drops again after the twelfth month to almost zero over the remaining duration of the entitlement frame. The development is very similar for the unemployed without ALMP, but because of the lower number of observations, the indicator is more volatile.

The **number of applications per week** represents the quantitative side of applications (Figure 5). Again, both the treated and control group start off in a very similar way, with the member of the treated group starting just above the control group. The number of applications per week gently drops till the 6th month and then picks up again. Apart from a remarkable increase at the very end of the entitlement period, the indicator is relatively stable.

According to theory, one would probably expect more of an upward trend over time, especially as the end of the entitlement period comes nearer. The application number seems to take the minimum requirement of the unemployment insurance (8 to 12 applications a month) as orientation. Case workers of the regional placement centre don't seem to pressure the unemployed into writing more applications as time passes by.

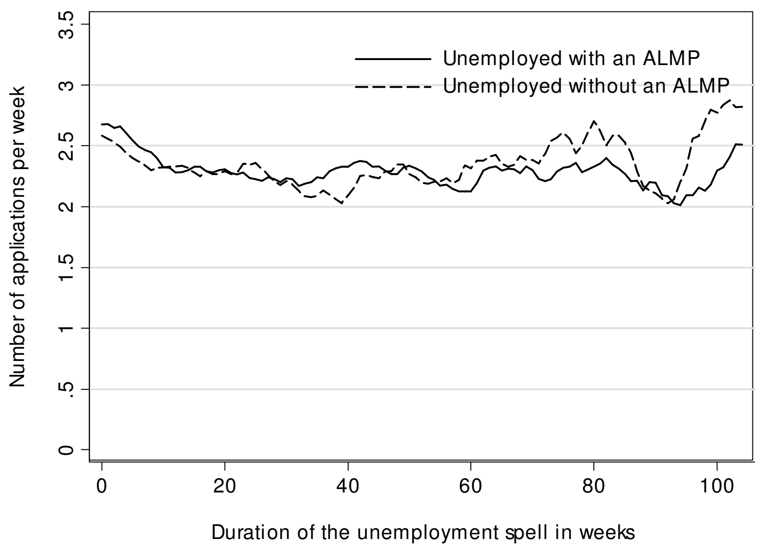

Figure 5: Search intensity

Note: The graph shows the average number of applications per week, giving equal weight to each unemployed registered in a certain week. The duration is plotted until the 104th week, after which the entitlement time frame expires. A total number of 738 unemployment spells are observed, 338 of which contain an ALMP participation at some stage of the spell ("unemployed with an ALMP"). Because of low observational numbers in certain weeks, a nine week moving average is used.

Summarizing, one can conclude that the differences between the two groups in all three indicators are very small. This is surprising as one would think behaviour and chances on the labour market as captured by the three indicators would be a main influence on the decision of ALMP participation. The closeness of the level and the development of the three indicators over the entire duration indicates that either a) the two groups are in fact very similar (i.e. that participation is random, at least in terms of labour market chances as captured by three indicators) and that the ALMPs have no influence at all, or b) that the ALMP participants actually do fare worse over time but that this is offset by the ALMPs.

6. Measuring the effect through Panel Regression

Unlike most studies on ALMP, which compare different persons with each other, the rich panel data at hand allows to compare applications of the same person over time. This eliminates a tremendous amount of unobserved heterogeneity. Because heterogeneity can be controlled for, widely understood statistical instruments like the regression method can be used, and there is no need to rely on strong assumptions.

Frame of Analysis
Whatever the estimation strategy or sample used, there are always three sets of regressions conducted in the following, one each for the three application indicators. For job interview probability the observational unit is the individual application and the dependent variable measures if the application resulted in a job interview (taking on the value 1 if successful, and 0 if unsuccessful). For the other two indicators, weekly number of interviews and applications, the panel is transformed so that the observational unit is one week of the unemployment spell. The unit shows the number of interviews or applications in that particular week.

The effect of the ALMP is captured by the regression coefficient of a dummy variable which indicates if the application was sent off before (0) or after the ALMP announcement (1). The announcement is chosen as the focal point as it divides the spell into a period before the application behaviour of the unemployed was influenced by a participation, and a period where it is influenced, therefore capturing all possible effects of the ALMP.

To calculate the coefficient of the effect dummy accurately, control variables are added to the model. The first set of control variables is a set of 13 duration dummies which indicate in which months the application was sent off (the dummies are: 1st month, 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months). For the number of applications per week, this is simply the month in the unemployment spell that particular week is part of. For interview probability and the number of interviews per week, the month in which the applications are sent off is relevant, and not the month in which the interviews occur; the dataset does not contain information about the date of the job interview (the indicator “interviews per week” is therefore the number of interviews achieved by the applications sent off in a certain week). These dummies capture the influence of time in a very flexible way. It is a very important set of control variables, as two of three application indicators fall steeply over time. Without the duration dummies, the results are heavily distorted. As applications after announcement are later in the spell than applications before announcement, the estimation wouldn't correctly distinguish between the effect and the influence of time.

An additional variable is added which indicates how many weeks before or after the ALMP announcement the application was sent off. If the application was sent off before the announcement, the value is negative. The variable thereby controls for any correlation between the ALMP effect and duration relative to the announcement (a cumulative effect for example). This model belongs to the family of event study models, which study the impact of an event on a variable of interest, often the stock price of a company (for a recent overview of this methodology, see Khotari and Warner 2006). It is common to document graphically the development of the indicators of interest around the "event", thereby identifying the short term effect. This is done in Figure 6. Because of high fluctuations, moving averages are used. These moving averages are calculated separately for the weeks before and the weeks after the announcement. The value for the week of the announcement is calculated with both the data from before and after the announcement. The graph shows that there is a positive gap between the two values, for both probability of a job interview and interviews per week (i.e. the value is higher when using the moving average based on data after the event). This simple descriptive analysis indicates that ALMPs have a positive effect. The number of applications in the week of the event on the other hand is a bit smaller when calculated as a moving average of the weeks after the announcement, indicating a negative effect of the ALMP on the search intensity.

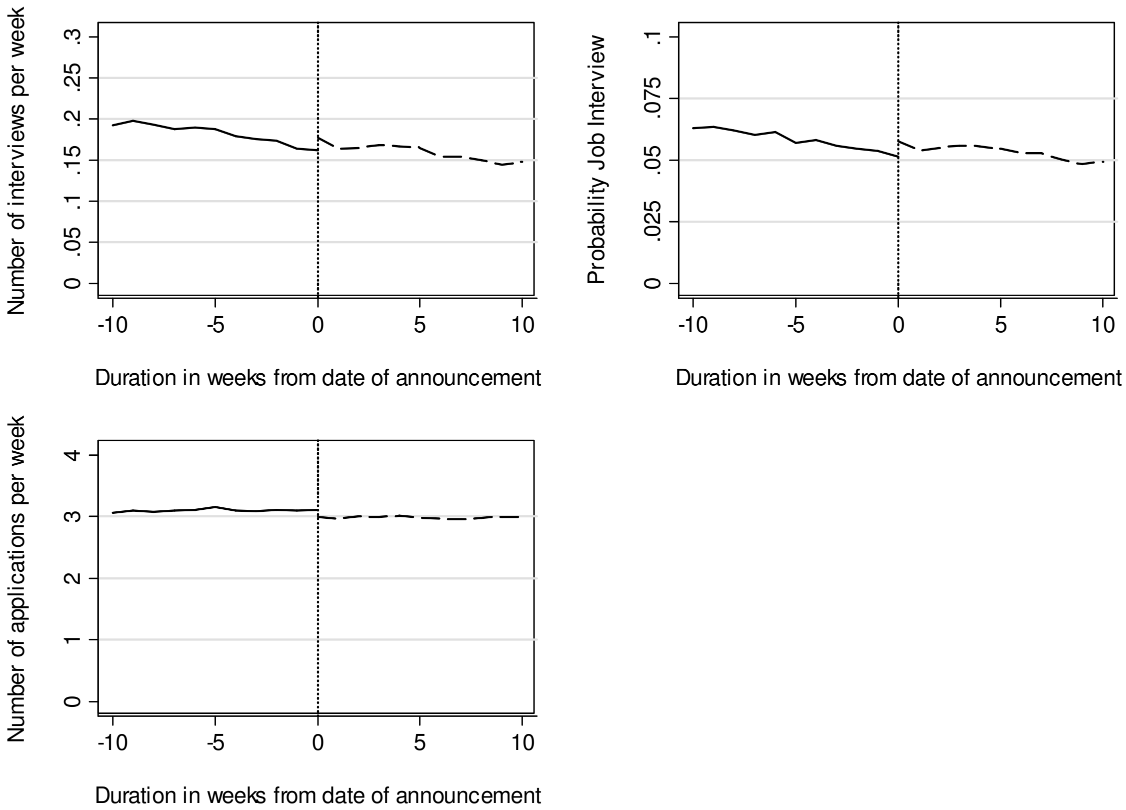

Figure 6: Development of the application indicators before and after the ALMP announcement

Note: The graph shows the average development in the three indicators ten weeks before to ten weeks after the ALMP announcement (the announcement is marked with a vertical line). Because of low observational numbers and high volatility in the indicators, a nine week moving average is used. The moving average is applied separately to the weeks before and the weeks after the announcement. The value for the week of the announcement (week 0) is calculated once through a moving average with data before the announcement and once with data after the announcement. Data from 203 unemployed was used (the effect can only be calculated for ALMP participants with at least one observed application before and one application after the announcement).

One more variable is added to the model, the unemployment rate in the occupation of the unemployed person who writes the application. This variable is measured on a monthly interval (e.g. for an application in September the unemployment rate of the occupation in September is used), and is calculated as the deviation from the median value. This variable is an important control variable as the state of the labour market might have both a large influence on the success of the application and on the performance of the ALMP. To prevent any bias, the control variable is added to the model. Finally, fixed effects are included, and thereby all time invariant differences between the unemployed are controlled for.

Note that the sets of control variables overall are parsimonious, only adding variables which would distort the calculations of the effect. The data is rich enough to add many other variables to the model, which would explain the outcome (for example the characteristics of the application). However, by adding more variables they are effectively held constant when estimating the effect. If the unemployed writes different types of applications after the ALMP, this should not be hold constant as it is part of the effect.

The estimation is done through Ordinary Least Square (OLS), and heteroskedasticity robust standard errors are reported. If not mentioned differently, data from all ALMP participants are used (there is no exclusion of outliers). All applications except the ones from the lay-off period and the last month are included. As described in the data section, these applications have to be dropped as both the lay-off period and the last month are subject to different rules by the unemployment insurance which would potentially distort the analysis.

Results

Table 2 shows the average effect of the ALMPs used at the Zurich-Staffelstrasse agency. The effect is large: An increase of 0.0308 in the number of interviews per week is the equivalent of 7.3 % when measured against the value of the constant, 0.4214. The constant can be interpreted as the number of interviews in the first month of unemployment. At the time the average ALMP is announced (104 days after the unemployment spell has started (median)) that baseline interview frequency has decreased to 0.2774 (measured as the sum of the constant and the coefficient for the dummy of the fourth month of unemployment). The relative effect is then the equivalent to a rise of 11.1 %.

The interview probability is increased by 0.0107, which is the equivalent of 7.0 % measured in the first month of unemployment, and 9.4 % after 104 days. The effect on applications per week is relatively small: The unemployed write 0.0972 applications per week more after the announcement. That is an increase of 3.6 % in the first month, or 3.9 % measured after 104 days. Both effects, the effect on interview probability and the one on search intensity, feed into the effect of the first indicator, interviews per week. However, changes in the number of interviews per week stem mainly from changes in the interview probability, while the search intensity increases just a little through the ALMP and has only a small influence on the increase in interviews per week.

Only the coefficient for the effect on interview probability is statistically significant (on the 10 %-level), despite the large size of the effect on interviews per week. The standard errors are large, indicating that there is considerable heterogeneity hidden behind the average effects. This heterogeneity will be further investigated below.

The control sets behave as assumed: The coefficients of the duration dummies are highly negative and increasing over time, at least when regressing on interviews per week and interview probability. This shows that these indicators are falling over the duration of the spell. The variable “application date relative to announcement” has a negative influence. This indicates that there might be a small interaction between the effect and the duration i.e. that the effect is decreasing over time. However, the coefficient is not significant and the effect relatively small. The unemployment rate in the profession of the unemployed person has a large negative influence on both interviews per week and the interview probability, but a small positive effect on the search intensity.

Dependent variable:	**Interviews per week**	**Interview Probability**	**Applications per week**
Mean	0.1355	0.0493	2.7478
Std. Dev.	0.4752	0.2165	1.6552
Overall ALMP Effect	0.0308	0.0107+	0.0972
(Dummy is 1 after ALMP announcement)	(0.0215)	(0.0061)	(0.0732)
Duration (omitted dummy: Month 1)			
Month 2	-0.1394**	-0.0344**	-0.1900
	(0.0394)	(0.0094)	(0.1273)
Month 3	-0.1596**	-0.0465**	-0.2278+
	(0.0426)	(0.0110)	(0.1350)
Month 4	-0.1440**	-0.0391**	-0.2239
	(0.0502)	(0.0134)	(0.1530)
Months 5 to 6	-0.1443*	-0.0420**	-0.2205
	(0.0560)	(0.0152)	(0.1783)
Months 7 to 8	-0.1674*	-0.0454*	-0.1811
	(0.0700)	(0.0194)	(0.2214)
Months 9 to 10	-0.1780*	-0.0516*	-0.0699
	(0.0838)	(0.0242)	(0.2687)
Months 11 to 12	-0.1691+	-0.0416	-0.1933
	(0.0974)	(0.0285)	(0.3166)
Months 13 to 15	-0.1903	-0.0506	-0.0773
	(0.1161)	(0.0338)	(0.3752)
Months 16 to 18	-0.2072	-0.0611	0.0045
	(0.1356)	(0.0400)	(0.4618)
Months 19 to 21	-0.2182	-0.0606	-0.0170
	(0.1557)	(0.0465)	(0.5393)
Months 22 to 24	-0.1699	-0.0370	-0.0751
	(0.1808)	(0.0541)	(0.6130)
Month 25 and more	-0.2820	-0.0722	0.1109
	(0.2040)	(0.0641)	(0.7272)
Application date relative to announcement (in weeks)	-0.0007	-0.0005	-0.0044
	(0.0020)	(0.0006)	(0.0066)
Unemployment rate in occupation	-0.0135**	-0.0056**	0.0103
(in percentage point deviation from the median rate)	(0.0052)	(0.0017)	(0.0174)
Fixed effects	yes	yes	yes
Constant	0.4214**	0.1532**	2.7351**
	(0.0879)	(0.0270)	(0.2695)
Sample			
All unemployed / only ALMP participants	ALMP	ALMP	ALMP
Number of applications or weeks	6518	17910	6518
Number of unemployed	338	338	338
Estimation			
OLS (with robust standard errors)	yes	yes	yes
R-squared	0.1178	0.1454	0.1864
F-value	4.8861	3.8608	3.2209

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
All applications except the ones from the lay-off period and the last month of unemployment are used.

Table 2: The ALMP effect on the three indicators

Although not all overall effects are statistically significant when measured as the average over all participants, there are some groups which gain heavily from the ALMP. The most important of these groups in terms of size and the gain through the ALMP is the group of the unemployed with a long term unemployment (LTU, i.e. a duration of more than 12 months) forecast. The forecast is an individual duration prediction recorded by the case worker at the start of the unemployment spell. Among ALMP participants, both groups of unemployed with a LTU forecast and unemployed ones are roughly of the same size. Annex 2 shows the characteristics of groups split according to the duration forecast. In average, the unemployed with a LTU forecast are older and worked more often in the hospitality industry and public administration. This group has an above average proportion of unemployed with no further education. In terms of ALMP, they participate more often in employment programmes and personality oriented courses, less often in Basic courses and language courses.

Because the two groups differ largely regarding the ALMP effect, the results are shown again in Table 3, this time with the sample split into two: One regression is conducted for the group with a forecast of more than 12 months (LTU); the other regression only uses data from the group with a forecast of less than 12 months (Non-LTU). The results show that the effect is very strong for unemployed with an LTU forecast while quite weak for the other group, no matter what indicator is examined. The group with a LTU forecast experiences an increase of 0.0386 interviews per week. Measured against their baseline number in month one (as measured by the constant), this effect is equivalent to 19.4 %. After 104 days, the effect is equivalent to an even larger increase of 27.6 %. Interview probability increases by 0.0132 (an increase of 23.5 % in the first month and 32.3 % after 104 days), once the ALMP has been announced. And the third indicator, applications per week, increases by 0.2071 (8.2 % in the first month, 8.7 % after 104 days). The effect of ALMP on the application indicators of participants with an LTU forecast is positive, very large and statistically significant.

Dependent variable:	**Interviews per week**		**Interview Probability**		**Applications per week**	
Subsample: Forecast =	**LTU**	**Non-LTU**	**LTU**	**Non-LTU**	**LTU**	**Non-LTU**
Mean	0.1033	0.1782	0.0382	0.0648	2.7034	2.7482
Std. Dev.	0.4073	0.5479	0.1917	0.2463	1.5657	1.6716
Overall ALMP Effect	0.0386+	0.0150	0.0132+	0.0043	0.2071*	0.0280
(Dummy is 1 after ALMP announcement)	(0.0216)	(0.0371)	(0.0069)	(0.0102)	(0.1012)	(0.1083)
Duration (13 dummies, omitted: Month 1)	yes	yes	yes	yes	yes	yes
Application date relative to announcement	yes	yes	yes	yes	yes	yes
Unemployment rate in occupation	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes
Constant	0.1991*	0.6253**	0.0562+	0.2425**	2.5145**	3.0000**
	(0.0901)	(0.1513)	(0.0289)	(0.0438)	(0.3662)	(0.4404)
Sample						
All unemployed / only ALMP participants	ALMP	ALMP	ALMP	ALMP	ALMP	ALMP
Number of applications or weeks	3496	2851	9451	7835	3496	2851
Number of unemployed	166	162	166	162	166	162
Estimation						
OLS (with robust standard errors)	yes	yes	yes	yes	yes	yes
R-squared	0.2748	0.1825	0.1864	0.1178	0.2244	0.1806
F-value	2.3576	3.1401	3.2209	4.8861	1.0121	0.7125

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used. The sample is split according to the duration forecast by the caseworker (LTU (long term unemployment): over 12 months).

Table 3: The ALMP effect for unemployed with (without) a Long Term Unemployment forecast

Unemployed with a forecast of less than 12 months on the other hand only show an increase of 0.0150 interviews per week (which is equivalent to 2.4 % after the first month, 3.0 % after

104 days), an increase in the interview probability of 0.0043 (1.8 %, 2.1 %) and an increase of 0.0280 applications per week (0.9 %, 1.0 %). The ALMP have also a positive effect on this group. Compared with the group with a LTU forecast, the effect pales though.

The next table (Table 4) shows the decomposition of the overall effect into its partial effects. The simple dummy measuring the overall effect is substituted by three dummies which switch to 1 when the application is written after the announcement and before the start of the ALMP (threat effect), or between start and end of the ALMP (lock-in effect) or after the ALMP has finished (skill enhancement and signal effect). Because they both happen at the same time, their combined impact is measured. The coefficients compare the effect relative to the situation before announcement.

Dependent variable:	**Interviews per week**			**Interview Probability**			**Applications per week**		
Subsample: Forecast =	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**
Mean	0.1355	0.1033	0.1782	0.0493	0.0382	0.0648	2.7478	2.7034	2.7482
Std. Dev.	0.4752	0.4073	0.5479	0.2165	0.1917	0.2463	1.6552	1.5657	1.6716
Partial Effects									
1. Threat Effect	0.0339	0.0159	0.0252	0.0097	0.0006	0.0071	0.1075	0.2495*	-0.0085
(Dummy is 1 between announcement and start ALMP)	(0.0274)	(0.0264)	(0.0435)	(0.0073)	(0.0080)	(0.0116)	(0.0855)	(0.1244)	(0.1217)
2. Lock-in Effect	0.0279	0.0508*	-0.0020	0.0118+	0.0203*	-0.0006	0.0865	0.1842+	0.0735
(Dummy is 1 between start and end ALMP)	(0.0233)	(0.0248)	(0.0430)	(0.0068)	(0.0079)	(0.0119)	(0.0839)	(0.1100)	(0.1288)
3. Skill enhancement and 4. signal effect	0.0269	0.0710*	-0.0168	0.0126	0.0308**	-0.0060	0.0678	0.1778	0.0300
(Dummy is 1 after the ALMP ended)	(0.0302)	(0.0331)	(0.0542)	(0.0088)	(0.0101)	(0.0154)	(0.1054)	(0.1406)	(0.1630)
Duration (13 dummies, omitted: Month 1)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Application date relative to announcement	yes	yes	yes	yes	yes	yes	yes	yes	yes
Unemployment rate in occupation	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	0.4213**	0.2038*	0.6344**	0.1531**	0.0579*	0.2456**	2.7368**	2.5078**	3.0038**
	(0.0880)	(0.0903)	(0.1542)	(0.0270)	(0.0288)	(0.0442)	(0.2696)	(0.3669)	(0.4427)
Sample									
All unemployed vs. ALMP unemployed	ALMP	ALMP	ALMP	ALMP	ALMP	ALMP	ALMP	ALMP	ALMP
Number of applications	6518	3496	2851	17910	9451	7835	6518	3496	2851
Number of unemployed	338	166	162	338	166	162	338	166	162
Estimation									
OLS (with robust standard errors)	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.2172	0.2754	0.1827	0.1454	0.1872	0.1179	0.2233	0.2245	0.1807
F-value	2.1041	2.1213	2.7494	3.4545	3.0716	4.2914	0.6704	0.9337	0.6584

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used. The sample is split according to the duration forecast by the caseworker (LTU (long term unemployment): over 12 months).

Table 4: The ALMP effect split into its partial effects

All partial effects result in sizeable changes on at least one indicator, but not all of them in the direction proposed by theory. Regarding the threat effect, there is indeed evidence of changes showing up on the indicator “applications per week” once the ALMP has been announced. The effect only exists for the group with a LTU forecast where it is strong (+ 9.9 % more applications per week, when measured against the constant). The group without a LTU forecast shows no sign of the threat effect.

The lock-in effect doesn't seem to exist at all. The unemployed don't seem to decrease their search intensity once the ALMP has started; on the contrary. The LTU group increases search efforts by 7.3 %. At the same time, the LTU group experiences a steep increase in the interview probability which overall results in a similarly steep increase on interviews per week. The group without a LTU forecast doesn't show any changes worth mentioning. The lack of a lock-in effect during the ALMP is not so much surprising from a practical point of view as many of the ALMPs include application training. If the lock-in effect exists at all, it is overlaid by the skill enhancement effect which might start even before the ALMP has finished.

Once the ALMP has finished, the positive effect is very large for the group with a LTU forecast. The leading indicator is interview probability, but there is also an increase in search intensity, compared with the situation before the announcement. For interviews per week and interview probability, the measured effect is at its strongest here, indicating the strong sustainability of the positive ALMP effect for this group.

The non-LTU group on the other hand shows negative effects for probability and interviews per week after the ALMP has finished. These effects are relatively small and don't differ significantly from zero. The negative effects could therefore be purely random. If a negative effect would remain in a larger sample, its most likely explanation would be that it stems from a negative signal sent out to potential employers.

Sensitivity analysis
A possible criticism questioning the validity of the results could be that the results are distorted because the composition of the observed group of unemployed changes over time. This criticism will be addressed in test 1. Further, while there are good reasons why the main estimation (Table 2 and 3) has been conducted with the specification chosen (those reasons will be stated below), it is interesting to see how robust the estimates are when the estimation strategy is changed. In order to test this, the main model is changed in six aspects. Test 2 observes how the estimates change when the panel structure is changed. The other tests incorporate changes regarding the duration variables (test 3), the observations used (dropping outliers in test 4 and personal applications with an unusual high success rate in test 5) and check the non-anticipation assumption (test 6).

A potential issue regarding the balance of the sample (test 1) is that the panel might become less balanced as unemployed with low chances remain in the pool and unemployed with above average chances leave because they find a job. If the ALMP has a better effect on unemployed with low chances (as shown in Table 3), the calculated average effect might overestimate the true effect of the ALMP. Figure 7 shows that the chances of the remaining pool of unemployed don't deteriorate as much as one might expect. For each person, the average of the three indicators before the announcement is calculated (pre-announcement value). At the moment of the announcement, the sample is complete; the average pre-announcement values over the whole sample of ALMP participants are an interview probability of 0.0632, 0.1857 interviews per week and 2.9264 applications per week. Each week after the announcement, the sample looses members. The sample average of the pre-announcement values falls because of the changes in the group composition; members with high pre-announcement values leave the group. As a benchmark, a second line in the graph represents what would happen if no members would have left the group (i.e. the attrition is corrected): the line is horizontal as the average value would stay constant. Figure 7 shows that there is some deviation of the uncorrected sample mean of pre-announcement values from that constant, but the difference is relatively small. With other words, the estimation of the ALMP effect should not be biased by an imbalance in the sample.

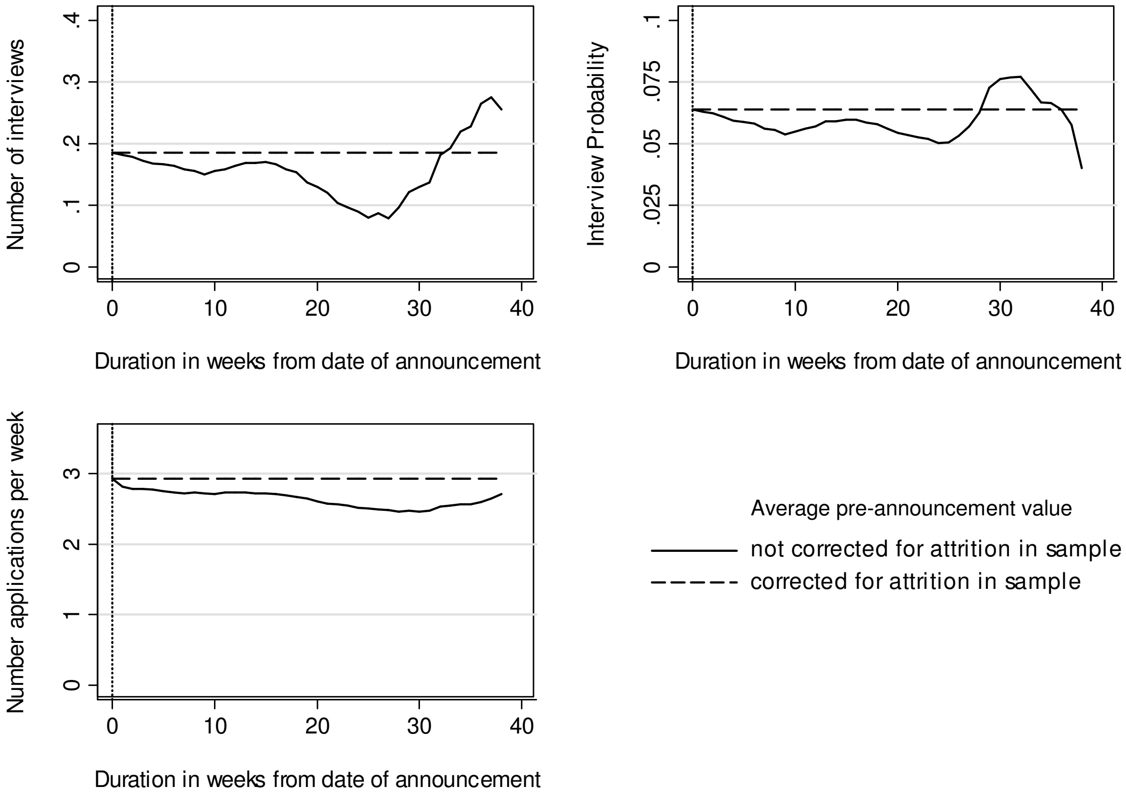

Figure 7: Assessment of sample attrition (development of pre-announcement values in sample)

Note: The duration is plotted until the 38th week after the announcement (the maximum for any person in the sample). A total number of 322 ALMP participants are observed (only ALMP participants with at least one observed application before the announcement can be assessed). Because of low observational numbers in certain weeks, a nine week moving average is used.

In terms of the balance between unemployed with a LTU forecast and unemployed without such a forecast, a similar conclusion can be made. As time progresses, an increasing number of applications might stem from unemployed with a LTU forecast. Again, changes in the balance of the sample over time might have an impact on the results: the calculated effect might be larger for unemployed with a LTU forecast because there are more applications after the announcement. The graph in Annex 3 shows how many applications stem from unemployed with a LTU forecast and how many applications from unemployed without such a forecast, and plots the development of these numbers over the duration of the unemployment spell. The balance does not change as quickly as one might have anticipated – the sample only changes its balance slowly. Finally, as part of this first test, the main model is recalculated (Annex 4). Instead of one dummy switching to 1 once the ALMP has been announced, this model entails three dummies: One switches to 1 between 0 and 10 weeks after the ALMP announcement and is zero before and after this period. The second dummy switches to 1 between 11 and 20 weeks after the ALMP announcement and the third dummy in week 21 and later. The results show clearly that the large difference between the effect on unemployed with LTU forecast and on unemployed without such a forecast is not just due to the fact that unemployed with LTU forecast tend to remain longer in the sample. The results show that in all three assessed periods after the announcement, the LTU forecast unemployed fare better than the Non-LTU ones.

Test 2 (Annex 5) shows what happens when all unemployed are added to the estimation, even the ones who haven't participated in an ALMP. The effects of the ALMP are smaller. The reason for this is that the model now assumes that the effect of duration is exactly the same for the ALMP-participants as for the rest of the unemployed. That is not necessarily true: Indeed, when using separate duration dummies for the treated and control groups, the coefficients of the separate duration dummies are quite different (not shown in the table). Using different duration sets for both groups, the size of the effect coefficients increase. There is no gain in adding the control group members to the regression, as they don't add any information on the size of the effect.

The third column shows the results when dropping the fixed effects and pooling all the applications. The same duration dummies are used for both groups here, but a new dummy variable is introduced, which switches to one if the unemployed writing the application is an ALMP participants at some stage of his or her spell (in the following referred to as the treated-dummy). The coefficient of this dummy is interesting, as it shows that there is large negative selection into the programs: The participants have a lower performance than non-participants in terms of interviews per week and interview probability, as shown by the negative coefficient of the treated-dummy. In the regression on the number of applications per week, the treated-dummy has a positive coefficient, indicating that ALMP participants write more applications than non-participants all other variables in the model kept constant.

In a last step of this test, many characteristics are added to the regression, which level out the differences in the application indicators between participants and non-participants which can be explained by these characteristics. The added variables are gender (dummy), Swiss/Foreigner (dummy), age (4 dummies), educational background (6 dummies), former industry (11 dummies) and knowledge of German (5 dummies). The separate duration dummies are kept in the regression. Indeed, through this the treated dummy is now almost zero for interview probability. It is even positive for applications per week and interviews per week, although the coefficient for the latter is small and not statistically significant. Together with the different sets of duration dummies, these variables seem to explain the differences in performance in the 3 application indicators rather well.

What happens to the coefficient of the effect dummy? The effects get stronger when moving from the regression with fixed effects to pooled regressions (apart from the regression on applications per week). Once the set of characteristics of the unemployed are added, the coefficient get smaller again, in fact to about the size they have in the standard specification, using fixed effects and only the data from ALMP participants (again, apart from applications per week). This shows that the core results are robust in terms of the estimation of the counterfactual development of the three application indicators, even when comparing applications of persons who participated in an ALMP with applications of unemployed who didn't participate.

The results of test 3 are shown in Annex 6. The standard model contains 13 dummies. This seems to be the best way to model the effect of time in a flexible way, allowing for non-linear influences. The results in Annex 6 show that if no time variables were used at all, the ALMP effects are smaller, in some regressions even negative. This downward shift of the effect coefficients is to be expected; as the effect dummy now partly includes the negative effect of time on the indicators (it does that since the applications after the announcement are by definition later in the spell than the applications before the announcement). The model is then tested by adding a more simple set of time dummies (only 5 instead of 13), and by adding two continuous variables (duration in weeks, duration in weeks squared). The effects tend to be weaker for the whole sample and even negative for the group without a LTU forecast. The effect for the group with LTU forecast on the other hand is quite robust. The test shows considerable robustness for the main finding; that ALMP should be used mainly for unemployed with low chances on the labour market.

Test 4 (Annex 7) looks at the influence of outliers. Outliers were not excluded in the main estimation as there was no reason to suspect that the ALMP effect would be different for them. To conduct test 3, the main results are recalculated, this time without unemployed who show at any stage of their unemployment spell more than 15 applications a week or 5 interviews per week. Unemployed with an overall interview probability above 0.75 are not covered. If the unemployment spell is longer than 2 years, it is cut off after this point. Overall, 314 applications are dropped (1.8 % of the observations), 19 of them from unemployed with a LTU forecast. Accordingly, the results for the participants with a LTU forecast changes very little (the effect becomes a bit stronger). For the group without the LTU forecast on the other hand, the effect gets weaker on two of the indicators. Again, the main conclusion, that ALMP should be mainly used for unemployed with a LTU forecast, remains valid.

Test 5 (Annex 8) recalculates the estimates, this time dropping all applications of unemployed who reported a success rate of 0.9 and higher for their personal applications. Such a high success rate is extremely unlikely and shows that the unemployed person has probably understood the term "interview" differently from the research team (as described in section 4). Through this, 130 applications of 7 unemployed are dropped. Leaving these applications away, the effect becomes larger for interview probability and interview per week when looking at the overall results and the results for group without a LTU forecast. The effect on interview per week almost doubles in size for unemployed without a LTU forecast. However, the effect remains considerably larger for unemployed with a LTU forecast.

The next test, test 6 (Annex 9), checks if the participants anticipated the ALMP. If that were the case, the threat effect would start to exert pressure well before the course was announced. In order to check for that a new dummy variable is introduced into the model. This dummy variable switches from 0 to 1 if the application was written during the month just before the announcement. If the participants don't anticipate the participation, the coefficient should be zero or close to it. The results show that the coefficients of this ‘placebo’ dummy are insignificant (even on the 10 %-level) in all nine estimations. Some of the coefficients are relatively large, but this could be either due to anticipation of the ALMP or due to random fluctuations. By introducing a dummy for the month before the announcement, the effect dummy now measures the difference between applications written until a month before the announcement and applications written after the announcement. The performance of the applications until a month before the announcement is slightly weaker than the average application before the announcement (as indicated by the positive placebo coefficients). Therefore, the estimated effect of the ALMP becomes larger in the placebo estimation. The average effect over all participants is now significant for the indicators interviews per week as well. The differences between the group with a LTU forecast and the group without one remain large.

Concluding over the six tests conducted, the results show that the coefficients are robust. The coefficients are particularly stable for the group of the LTU-unemployed. The coefficients for the non-LTU group vary and even change signs, but generally stay small. The main result, that the effect is much larger for the LTU group, holds throughout all changes.

7. Who gains?

The regressions in the last section show the average effect over all participants, the effect over the unemployed with a LTU forecast and the effect over unemployed without such a forecast. Because of its panel structure, the data set allows venturing beyond these average results by calculating individual treatment effects for each participant. This is useful because it gives further insights into which groups gain most from ALMP.

Technically, the individual effects are calculated using the residuals after estimating the main models (Table 2). The residuals capture everything which cannot be explained through the average treatment effects, the duration dummies, the application date relative to announcement, the unemployment rate in the occupation and the fixed effect. Latter makes sure that any time-invariant personal characteristics are not part of the residual. The only systematic component in the residuals should therefore be the personal treatment effect, measured as the deviation from the average effect. It is captured by calculating the difference between the mean of all the residuals before the announcement and the mean of all the residuals after the announcement. In order to calculate the absolute individual treatment effect, the difference is simply added to the average ALMP effect. Note that the effect can only be calculated for participants with at least one observed application before the ALMP announcement and one observed application after the announcement. Altogether, the individual effects can be calculated for 203 unemployed.

Figure 8 shows the average ALMP effect on the three application indicators. It illustrates that there are many winners, but also some losers among the participants.

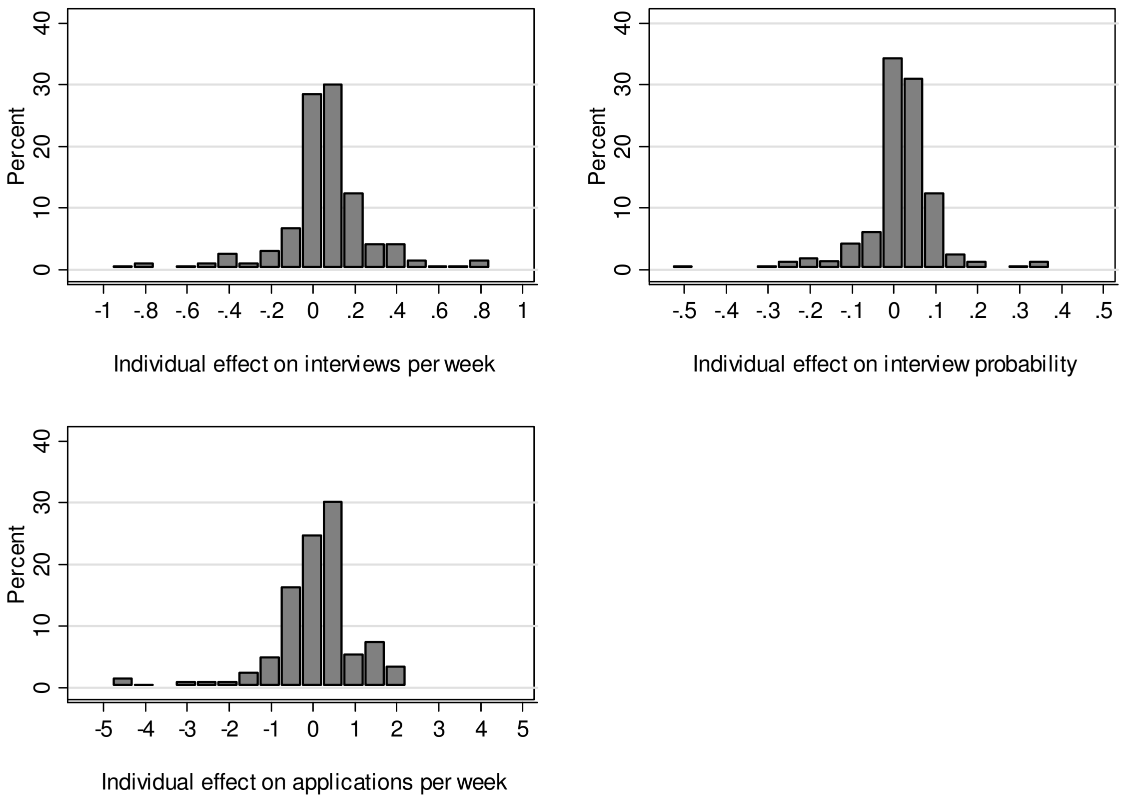

Figure 8: Distribution of the individual effects

Note: The graph shows the distribution of the ALMP effect on the three indicators (as calculated from the estimation in Table 2). Data from 203 unemployed was used (the effect can only be calculated for participants with at least one observed application before the ALMP announcement and one observed application after the announcement). Extreme outliers are not shown in the graphs (interview probability: four persons below 0.5 and one above 0.5; applications per week: one below -5 and two above 5; interviews per week: seven below -1 and three above 1).

Regressions can now be run, explaining the individual effects through different independent variables to see under what circumstances the ALMP effect is increased or diminished. The first set of independent variables used is a set of ALMP type dummies (Table 5). In order not to overstretch the number of observations, each category of ALMP entails at least 16 unemployed persons. This is admittedly a very low number still, so the results are only preliminary. The categories used are "basic course" (which focuses on situation analysis, general information about unemployment and application training), "personality oriented course" (assessing and developing soft skills), "basic qualification course" (alphabetization and very basic German), "language course" (German courses), "other courses" (IT courses and vocational training for different industries) and "employment programmes" (workplaces for the unemployed with a training component). The observational number is indicated in parentheses in Table 5).

The different ALMP types have very different effects. The results show that the omitted category, basic course, has strong positive effects on all three indicators (its coefficient are shown by the constant). Interviews per week rises by 0.0791 (the overall ALMP effect for the assessed group of the 203 unemployed is 0.0281), interview probability by 0.0277 (overall

0.0114) and applications per week by 0.1242 (0.0940). Against the strong performance of this ALMP type which is also the most commonly used one, all other types fare worse, at least in terms of interview probability and interviews per week (the ALMP type coefficients show the relative performance compared to the omitted category, the basic course).

Apart from the basic course, basic qualifications courses and "other course" also do well. The effect of the language courses is around zero as can be seen by adding the coefficients of the constant and the coefficient of the language course. Employment programmes and personality oriented courses do even worse, resulting in a negative effect on the application performance of its participants.[1] It might surprise that the effect of these two ALMP types is not just zero but negative (many previous evaluations actually identify negative impacts of programs, see Sianesi 2008). This negative effect can stem from a decrease in motivation through the announcement (as part of the threat effect), a lower number of applications while on an ALMP (lock-in effect) and/or a bad signal sent to potential employers when adding the course diploma to the application (see Falk et al. 2005). The observational number is too low in order to measure the partial effects on a program type base.

Dependent variable: Individual ALMP effect on	**Interviews per week**	**Interview Probability**	**Applications per week**
Mean	0.0281	0.0114	0.0940
Std. Dev.	0.5520	0.1532	1.3052
ALMP Type (omitted: Basic course (90 participants))			
Personality oriented course (30 participants)	-0.1363	-0.0569	0.0311
	(0.1152)	(0.0393)	(0.2389)
Basic qualifications course (16 participants)	-0.0346	-0.0040	-0.0397
	(0.0722)	(0.0154)	(0.2298)
Language course (17 participants)	-0.0815	-0.0216	-0.3994
	(0.1179)	(0.0286)	(0.3735)
Other course (18 participants)	-0.0699	-0.0021	0.0442
	(0.1584)	(0.0471)	(0.2865)
Employment programme (32 participants)	-0.0959	-0.0355	-0.0135
	(0.1050)	(0.0338)	(0.2192)
Constant	0.0791	0.0277+	0.1242
	(0.0702)	(0.0151)	(0.1795)
Sample			
All unemployed vs. ALMP unemployed	ALMP	ALMP	ALMP
Number of unemployed	203	203	203
Estimation			
OLS (with robust standard errors)	yes	yes	yes
R-squared	0.0088	0.0193	0.0076
F-value	0.4576	0.7455	0.3126

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
Data from 203 unemployed used (the effect can only be calculated for participants with at least one observed application before the ALMP announcement and one observed application after the announcement).

Table 5: The effect of different types of ALMP

Note that all coefficients but one (the effect of the basic course on interview probability) are insignificant, despite their large size. This means that not all participants have the same gain

[1] Interestingly, those two ALMP types are also the longest ones. This raises the questions if the lock-in effect is responsible for the weak performance. This doesn't seem to be the case, as the search intensity as measured by the number of applications per week is not reduced during these two types. Rather, it is the interview probability which is decreased during and after the ALMP.

from the ALMP types and there is a lot of variation in these individual effects, even when split up according to the ALMP type. Since the observational number is quite small, one would probably obtain significant differences with a larger sample.

In order to find out under what circumstances the ALMP work best, characteristics can be added to the regression. The dataset is very rich and allows for a multitude of factors to be tested (both characteristics of the unemployed person and the ALMP). However, the influence of many of those factors is not large enough to be significant on basis of the small observational set.

Table 6 shows how different characteristics of the unemployed person influence the ALMP effect. In the first block entered are three age group dummies. The results show that ALMP work best for the unemployed below the age of 30 (the omitted category). The coefficients are not statistically significant however, despite the considerable size of the coefficients. The next variables entered indicate the highest education the unemployed has attained. The results show that the higher the education of the unemployed, the better the results. The worst results show unemployed with no further education at all and unemployed with an apprenticeship, the best result unemployed with a university degree. This is surprising, because there is a broad choice of ALMP for unskilled persons.

Foreigners and women experience a larger effect on the number of interviews per week than Swiss and men: Foreigners gain more than Swiss because the ALMP results in a larger change in the search intensity, while women have a higher increase on interview probability than men. If the unemployed searches for a job in the same occupation as previously held (overall 73 % of all ALMP participants), he or she shows a much better ALMP effect. A search for a job in the same occupation increases the ALMP effect on interviews per week by 0.1484, the effect on interview probability by 0.0666 (significant on the 10 %-level) and the effect on applications per week by 0.1389 compared to searching a job in another occupation. This sheds a critical light on retraining and participants learning new skills because they cannot or do not want to go back to their old occupation. One could argue that this is merely an indication for motivation, but this effect is measured separately through the next variable. Motivation to participate in the ALMP has a strong positive effect, but the difference between motivated and unmotivated unemployed is not statistically significant. After controlling for motivation, the coefficient for the dummy which indicates if the person has been sanctioned once or several times during the unemployment spell is almost zero.

As a last characteristic, the forecast of the case worker on duration is added to the regression. Three groups are used here, and the gains for persons with a longer duration forecast seem to hold even if comparing persons with 0 to 5 months forecasts with the ones of 7 to 11. Comparing the two extreme ends, unemployed with 0 to 5 months forecasts and those with a LTU forecast, the following differences are statistically significant: The ALMP effect on interviews per week is 0.2069 higher. This is an enormous difference, considering the average effect is 0.0281.

Dependent variable: Individual ALMP effect on:	Interviews per week	Interview Probability	Applications per week
Mean	0.0281	0.0114	0.0940
Std. Dev.	0.5520	0.1532	1.3052
Age (omitted: below 30)			
Age 30 - 39	-0.0144	-0.0169	0.2621
	(0.0857)	(0.0254)	(0.3988)
Age 40 to 49	-0.1660	-0.0457	0.0391
	(0.1183)	(0.0310)	(0.3229)
Age 50 and older	-0.1164	-0.0544	0.0575
	(0.0985)	(0.0340)	(0.3089)
Education (omitted: no further education)			
Apprenticeship	-0.0171	0.0080	-0.0030
	(0.1483)	(0.0337)	(0.2184)
Gymnasium	0.1566	0.0425	0.1491
	(0.1096)	(0.0347)	(0.3116)
Technical college	0.2393*	0.0677+	0.4153
	(0.1036)	(0.0346)	(0.3600)
University	0.2644*	0.0459+	0.6861
	(0.1208)	(0.0275)	(0.9044)
Education not known	0.1171	0.0237	0.1596
	(0.1242)	(0.0388)	(0.4079)
Of foreign origin	0.0444	-0.0118	0.2508
	(0.1146)	(0.0281)	(0.2537)
Woman	0.0474	0.0237	-0.2798
	(0.0800)	(0.0207)	(0.2115)
Former industry (12 dummies)	yes	yes	yes
Participant is searching for a job in the same profession than previously held	0.1484	0.0666+	0.1389
	(0.1147)	(0.0385)	(0.2460)
Not motivated to participate in ALMP	-0.0846	-0.0225	-0.2271
	(0.0805)	(0.0204)	(0.4329)
Sanctioned at least once during spell	-0.0003	-0.0102	-0.1267
	(0.0920)	(0.0264)	(0.2612)
Unemployment duration forecast (omitted: Forecast 12 months and more & forecast unknown)			
Forecast 0 to 5 months	-0.2069+	-0.0590	-0.3772
	(0.1171)	(0.0367)	(0.2708)
Forecast 6 to 11 months	-0.1585	-0.0384	-0.1540
	(0.0997)	(0.0298)	(0.1972)
Constant	-0.0872	0.0042	-0.1843
	(0.2077)	(0.0583)	(0.5449)
Sample			
All unemployed vs. ALMP unemployed	ALMP	ALMP	ALMP
Number of unemployed	203	203	203
Estimation			
OLS (with robust standard errors)	yes	yes	yes
R-squared	0.1185	0.1278	0.0873
F-value	1.2388	1.3751	0.7564

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
Data from 203 unemployed used (the effect can only be calculated for participants with at least one observed application before the ALMP announcement and one observed application after the announcement).

Table 6: The influence of different characteristics on the ALMP effect

One has to keep in mind that Table 5 shows the effect the way the ALMP types are currently used on the unemployed of the Zurich-Staffelstrasse agency. These estimates do not just tell a story about the ALMP itself, but also about its participants and how well they are adapted to the course itinerary. To improve performance of the ALMP types, one can adapt the ALMP to the existing participants, or select the participants differently for an existing ALMP, or one can do both.

8. Getting a job

A possible criticism to the new approach could be the fact that job interviews only provide a stepping stone on the way to find a new job and end unemployment. While this is true by definition, a job interview takes a job seeker a far way, as the data shows. The following numbers are based on the data of all unemployed who left unemployment with a job and who started the spell after 1st of July 2007 and ended it before 31st of March 2008. Only for this group the entire application history from start till end of the unemployment spell is known. This group only entails 76 unemployed; because of the low number of observations, the following results cannot be further assessed for subgroups (e.g. ALMP participants vs. non-participants, unemployed with LTU forecast vs. Non-LTU forecast etc.).

The average person who left unemployment with the opportunity to start a new job wrote 36 applications (median value). Please note that this is a group with above average chances, because they found a job during the nine months of unemployment monitored. The probability of getting the job when writing an application is therefore 5.2 %. Within that process, the biggest hurdle is getting a job interview. In average, it took the unemployed 7.1 applications for each job interview (median), resulting in a probability of 14.1 %. It then took them in average 2 interviews (median) to actually get a job. The chances of a job, given an interview, are 50.0 %.

	Median	**Mean**
Probability job interview given an application	0.1409	0.2038
Probability job offer given a job interview	0.5000	0.5372
Probability job offer given an application	0.0520	0.1065
Number of unemployed	76	76
Number of applications	2,053	2,053

Notes: The table only captures unemployed who i) left unemployment with a job and ii) started unemployment on 1 July 2007 or later and finished their spell on 30 March 2008 or earlier. Thereby, all applications of a person could be recorded in the database. Because of these selection criteria, the reduced sample is not representative for the overall sample.

Table 7: Probability of getting a job (reduced sample)

The relative impact of the ALMPs on the overall probability of a job remains exactly as measured by the different regressions in this study, as long the ALMP doesn’t change the probability of a job interview. This is unlikely of course, as most acquired know-how would work both when writing the application and in the job interview environment (e.g. language skills, self assurance, showing newly acquired job skills). It is therefore plausible that the ALMP effect on the probability of a job interview is are going have an effect on the probability of the job, given an interview, as well.

It is difficult to envisage a characteristic which has a positive impact on getting to an interview, but then a negative one on getting the job (or the other way round). The calculated effects on the probability of a job interview can therefore be taken as a lower boundary of the overall effect on getting a job.

9. Conclusion

While many previous studies applied methods which had to rely on strong assumptions in order to calculate accurate and unbiased estimates of the ALMP effect, the new approach used in this study doesn't. This is possible through the use of new indicators and data, which allows measuring the outcome several times before, during, and after the ALMP. This allows excluding time-invariant characteristics and to solve the selection bias.

The new instrument can be relatively easily applied to measure the effect of ALMPs by labour market institutions, as it combines several good controlling characteristics: It is a detailed, accurate and unbiased instrument utilizing relatively simple statistical tools. It can be easily understood by the persons responsible for the controlling process and communicated to involved partners. This makes it a trustworthy controlling instrument. It is inexpensive; the biggest cost involved is that the case worker has to update the application sheets (that is not just a cost though as it shows to the unemployed that these sheets are taken seriously). It can be easily updated on a regular base. This is an important characteristic as the ALMP might have different effects depending on the condition of the labour market (McVicar and Podivinsky 2008).

The method was applied as a trial run in one agency in Switzerland, the Zurich-Staffelstrasse agency. 30,000 applications were collected, along with much information on the unemployed and the ALMP used. Through this, a very rich dataset could be assembled. Estimates based on this data show that on average, the ALMPs have a strong positive effect on the chances of a job interview, the weekly number of applications and the weekly number of interviews when applied to unemployed with a long term unemployment forecast. Applied to unemployed without such a forecast, the ALMP show relatively little impact. There are stark differences between the ALMP types as well. While most types do well, personality oriented courses and employment programmes have a negative impact on the application performance of the unemployed. These are preliminary results of course since they stem from the unemployed of a single agency.

In order to gain more insight into the ALMPs and to start using the proposed method as a controlling tool, more data now needs to be collected. It is worth the effort: ALMPs are an expensive tool in financial terms. If they don’t work, they are costly in human terms too, because both the participants and the case worker hope that these programs will shorten unemployment. It is time to start controlling this instrument thoroughly and on the basis of quantitative data, and thereby improve its quality and reputation.

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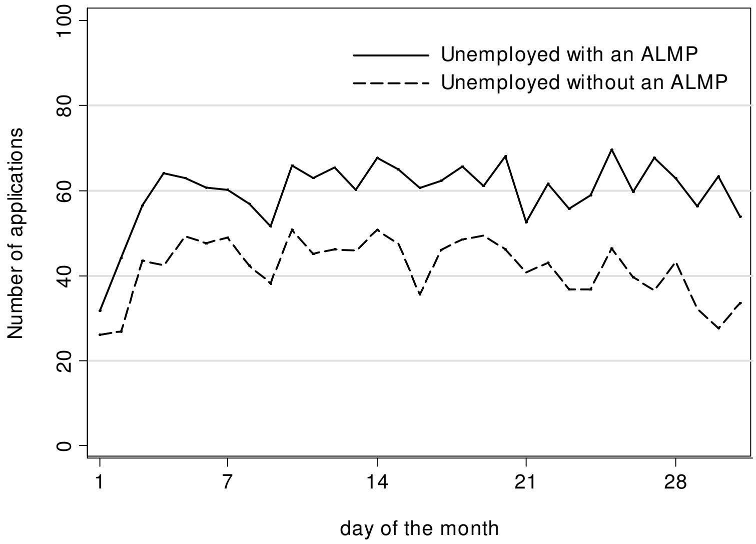
Annex

Annex 1: Applications recorded in a typical month at the Zurich-Staffelstrasse agency



Note: Averages over the nine month of data collection are shown. Day 30 and day 31 were reweighed because their lower number of appearance. December was not taken into account.

Annex 2: Characteristics of ALMP participants

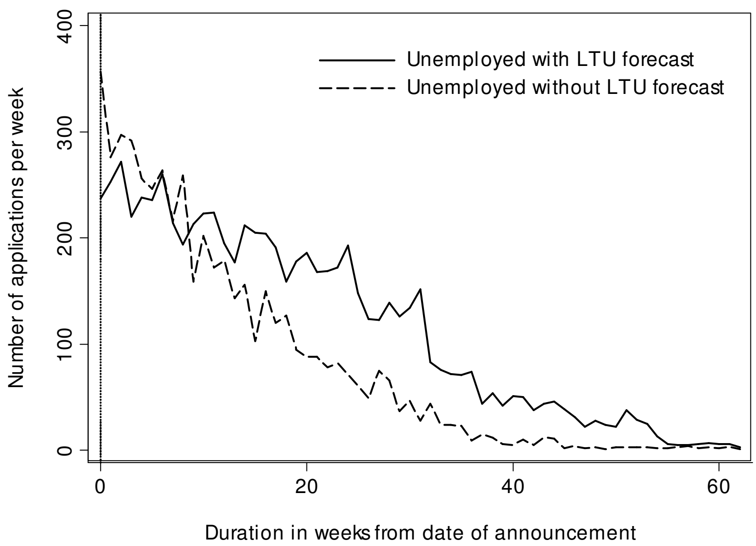
Unemployment duration forecast:	0-6 months	7-12 months	13 and more months	no forecast
Age	35.20	39.58	42.54	44.70
Women	0.57	0.44	0.48	0.20
Swiss	0.50	0.49	0.48	0.60
Industry				
No answer, first sector or “private household	0.35	0.18	0.14	0.00
Industry	0.11	0.06	0.08	0.30
Building and Constructing	0.07	0.21	0.14	0.00
Trade and Commerce	0.19	0.18	0.22	0.10
Hospitality industry	0.02	0.05	0.06	0.10
Transport and Communication	0.04	0.03	0.03	0.10
Financial services	0.13	0.09	0.12	0.30
Business services (incl. IT)	0.04	0.02	0.02	0.00
Public administration	0.02	0.03	0.04	0.10
Health and social services	0.02	0.07	0.07	0.00
Other services	0.02	0.09	0.07	0.00

Annex 2: Characteristics of ALMP participants (continued)

Unemployment duration forecast:	0-6 months	7-12 months	13 and more months	no forecast
Highest attained educational				
no further education	0.35	0.40	0.50	0.40
Apprenticeship	0.22	0.19	0.19	0.30
Gymnasium	0.02	0.06	0.05	0.10
Technical college	0.15	0.16	0.07	0.00
University	0.15	0.07	0.08	0.20
Education not known	0.11	0.11	0.10	0.00
ALMP				
Basic course	0.63	0.54	0.31	0.30
Personality oriented course	0.06	0.11	0.16	0.30
Basic qualifications course	0.06	0.06	0.07	0.00
Language course	0.11	0.08	0.05	0.10
Other course	0.06	0.07	0.08	0.00
Employment programme	0.09	0.13	0.33	0.30
N	54	108	166	10

Note: Only unemployed with an ALMP at some stage of their spell are covered. Apart from age, baseline probability, ALMP treatment effect and the number of observations, all numbers are proportions

Annex 3: Sensitivity test 1 - development of the number of applications after the announcement



Note: The graph shows the total number of applications per week sent out by any of the 338 ALMP participants. The duration is plotted until the 62nd week after the ALMP announcement (this is the maximum duration for any person in the sample).

Annex 4: Sensitivity test 1 - model including “time since announcement” interaction terms

Dependent variable:	**Interviews per week**			**Interview Probability**			**Applications per week**		
Subsample: Forecast =	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**
Mean	0.1355	0.1033	0.1782	0.0493	0.0382	0.0648	2.7478	2.7034	2.7482
Std. Dev.	0.4752	0.4073	0.5479	0.2165	0.1917	0.2463	1.6552	1.5657	1.6716
Effects split according to time since announcement									
1. Effect between week 0 and 10 after announcement (Dummy is 1 from week 0 to week 10)	0.0067 (0.0058)	0.0223** (0.0069)	-0.0110 (0.0098)	0.0476 (0.0726)	0.0750 (0.0947)	0.0622 (0.1094)	0.0189 (0.0204)	0.0559** (0.0212)	-0.0224 (0.0357)
2. Effect between week 11 and 20 after announcement (Dummy is 1 from week 11 to week 20)	0.0005 (0.0081)	0.0290** (0.0098)	-0.0282* (0.0144)	0.0680 (0.1038)	0.1147 (0.1302)	0.0707 (0.1677)	-0.0065 (0.0272)	0.0719* (0.0302)	-0.0907+ (0.0492)
1. Effect after week 20 (Dummy is 1 from week 20 to end of spell)	-0.0148 (0.0113)	0.0221 (0.0138)	-0.0526* (0.0212)	0.1268 (0.1368)	0.2649 (0.1688)	-0.0068 (0.2325)	-0.0319 (0.0372)	0.0737+ (0.0416)	-0.1517* (0.0703)
Control variables (duration; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)									
Number of applications	17910	9451	7835	6518	3496	2851	6518	3496	2851
Number of unemployed	338	166	162	338	166	162	338	166	162
Estimation (OLS with robust standard errors)									
R-squared	0.1457	0.1873	0.1183	0.2231	0.2240	0.1808	0.2175	0.2755	0.1834
F-value	4.1454	3.4978	4.8996	0.5850	0.8926	0.7119	2.2975	2.3413	3.2033

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used. The sample is split according to the duration forecast by the caseworker (LTU (long term unemployment): over 12 months).

Annex 5: Sensitivity test 2 – on selectivity

Annex 5a) All unemployed

Dependent variable:	Interviews per week				Interview Probability				Applications per week			
Overall Effect ALMP	0.0282	0.0334	0.0397*	0.0266	0.0087	0.0113+	0.0147**	0.0092*	0.0949	0.1100	0.0534	0.0342
(Dummy is 1 after ALMP announcement)	(0.0219)	(0.0215)	(0.0171)	(0.0171)	(0.0058)	(0.0061)	(0.0047)	(0.0047)	(0.0722)	(0.0732)	(0.0565)	(0.0570)
Duration												
Specification 1: 13 dummies (same for treated and control)	yes	no	no	no	yes	no	no	no	yes	no	no	no
Specification 2: 13 dummies (different for treated and control)	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
Panel or pooled estimation												
Fixed effects	yes	yes	no	no	yes	yes	no	no	yes	yes	no	no
Pooled, specification 1 (treatment dummy)	no	no	yes	no	no	no	yes	no	no	no	yes	no
Pooled, specification 1 (treatment dummy and characteristics)	no	no	no	yes	no	no	no	yes	no	no	no	yes
Treatment dummy (ALMP at some stage of the spell)			-0.0094	0.0112			-0.0106	-0.0019			0.1984+	0.2173*
			(0.0312)	(0.0310)			(0.0078)	(0.0078)			(0.1032)	(0.1033)
Control variables (application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (all unemployed incl. unemployed without ALMP)												
Number of applications	10805	10805	10805	10805	29991	29991	29991	29991	10805	10805	10805	10805
Number of unemployed	738	738	738	738	738	738	738	738	738	738	738	738
Estimation (OLS with robust standard errors)												
R-squared	0.2684	0.2687	0.0161	0.0421	0.1659	0.1663	0.0086	0.0246	0.2433	0.2440	0.0090	0.0195
F-value	3.2042	1.9958	6.7740	9.4412	4.4365	3.1683	9.9932	15.1264	0.8662	0.8245	3.7452	4.2857

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The pooled specification 1 lacks the individual fixed effects from the standard model but contains an extra dummy describing if the unemployed participates in an ALMP at any time during his or her spell (treated dummy). The pooled specification 2 is like specification 1, but contains further variables: gender (dummy), Swiss/Foreigner (dummy), age (4 dummies), educational background (6 dummies), former industry (11 dummies) and knowledge of German (5 dummies). The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used.

Annex 5b) All unemployed with a LTU forecast

Dependent variable:	Interviews per week				Interview Probability				Applications per week			
Overall Effect ALMP	0.0374+	0.0435*	0.0496*	0.0544*	0.0125+	0.0151*	0.0179**	0.0183**	0.2033*	0.2106*	0.1203	0.1255
(Dummy is 1 after ALMP announcement)	(0.0216)	(0.0216)	(0.0218)	(0.0218)	(0.0067)	(0.0069)	(0.0061)	(0.0061)	(0.0967)	(0.1009)	(0.0783)	(0.0794)
Duration												
Specification 1: 13 dummies (same for treated and control)	yes	no	no	no	yes	no	no	no	yes	no	no	no
Specification 2: 13 dummies (different for treated and control)	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
Panel or pooled estimation												
Fixed effects	yes	yes	no	no	yes	yes	no	no	yes	yes	no	no
Pooled, specification 1 (treatment dummy)	no	no	yes	no	no	no	yes	no	no	no	yes	no
Pooled, specification 1 (treatment dummy and characteristics)	no	no	no	yes	no	no	no	yes	no	no	no	yes
Treatment dummy (ALMP at some stage of the spell)			0.0448	0.0534			0.0091	0.0138			0.2593	0.2159
			(0.0522)	(0.0512)			(0.0134)	(0.0133)			(0.1876)	(0.1866)
Control variables (application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (all unemployed incl. unemployed without ALMP)												
Number of applications	5497	5497	5497	5497	14938	14938	14938	14938	5497	5497	5497	5497
Number of unemployed	294	294	294	294	294	294	294	294	294	294	294	294
Estimation (OLS with robust standard errors)												
R-squared	0.2728	0.2751	0.0121	0.0629	0.1982	0.1998	0.0085	0.0434	0.2380	0.2403	0.0128	0.0380
F-value	1.4806	1.5549	2.5685	7.3164	2.3966	2.3529	4.9068	13.5115	0.5799	0.9089	2.7294	4.3053

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The pooled specification 1 lacks the individual fixed effects from the standard model but contains an extra dummy describing if the unemployed participates in an ALMP at any time during his or her spell (treated dummy). The pooled specification 2 is like specification 1, but contains further variables: gender (dummy), Swiss/Foreigner (dummy), age (4 dummies), educational background (6 dummies), former industry (11 dummies) and knowledge of German (5 dummies). The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used.

Annex 5c) All unemployed without a LTU forecast

Dependent variable:	**Interviews per week**				**Interview Probability**				**Applications per week**			
Overall Effect ALMP	0.0109	0.0166	0.0373	0.0113	0.0004	0.0038	0.0152*	0.0052	0.0446	0.0531	-0.0339	-0.0609
(Dummy is 1 after ALMP announcement)	(0.0381)	(0.0372)	(0.0273)	(0.0277)	(0.0097)	(0.0103)	(0.0074)	(0.0075)	(0.1089)	(0.1090)	(0.0830)	(0.0846)
Duration												
Specification 1: 13 dummies (same for treated and control)	yes	no	no	no	yes	no	no	no	yes	no	no	no
Specification 2: 13 dummies (different for treated and control)	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
Panel or pooled estimation												
Fixed effects	yes	yes	no	no	yes	yes	no	no	yes	yes	no	no
Pooled, specification 1 (treatment dummy)	no	no	yes	no	no	no	yes	no	no	no	yes	no
Pooled, specification 1 (treatment dummy and characteristics)	no	no	no	yes	no	no	no	yes	no	no	no	yes
Treatment dummy (ALMP at some stage of the spell)			0.0022	0.0293			-0.0048	0.0028			0.0991	0.1442
			(0.0432)	(0.0435)			(0.0108)	(0.0109)			(0.1315)	(0.1328)
Control variables (application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (all unemployed incl. unemployed without ALMP)												
Number of applications	4935	4935	4935	4935	13923	13923	13923	13923	4935	4935	4935	4935
Number of unemployed	411	411	411	411	411	411	411	411	411	411	411	411
Estimation (OLS with robust standard errors)												
R-squared	0.2620	0.2619	0.0193	0.0396	0.1432	0.1437	0.0098	0.0221	0.2257	0.2268	0.0098	0.0239
F-value	3.6299	2.1427	3.8630	4.1065	4.9027	3.2091	5.5097	6.3848	0.8542	0.7017	1.9471	2.4457

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The pooled specification 1 lacks the individual fixed effects from the standard model but contains an extra dummy describing if the unemployed participates in an ALMP at any time during his or her spell (treated dummy). The pooled specification 2 is like specification 1, but contains further variables: gender (dummy), Swiss/Foreigner (dummy), age (4 dummies), educational background (6 dummies), former industry (11 dummies) and knowledge of German (5 dummies). The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used.

Annex 6: Sensitivity test 3 – changing the duration modelling

Annex 6a) All ALMP participants

Dependent variable:	Interviews per week				Interview Probability				Applications per week			
Overall Effect ALMP	0.0308	-0.0014	0.0117	0.0127	0.0107+	0.0011	0.0067	0.0062	0.0972	0.0305	0.0640	0.0330
(Dummy is 1 after ALMP announcement)	(0.0215)	(0.0221)	(0.0219)	(0.0224)	(0.0061)	(0.0056)	(0.0060)	(0.0058)	(0.0732)	(0.0730)	(0.0731)	(0.0741)
Duration												
Specification 1: 13 Dummies (standard)	yes	no	no	no	yes	no	no	no	yes	no	no	no
Specification 2: No time dummies	no	yes	no	no	no	yes	no	no	no	yes	no	no
Specification 3: 5 dummies	no	no	yes	no	no	no	yes	no	no	no	yes	no
Specification 4: 2 variables (duration, duration squared)	no	no	no	yes	no	no	no	yes	no	no	no	yes
Control variables (application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)												
Number of applications	6518	6518	6518	6518	17910	17910	17910	17910	6518	6518	6518	6518
Number of unemployed	338	338	338	338	338	338	338	338	338	338	338	338
Estimation (OLS with robust standard errors)												
R-squared	0.2172	0.2132	0.2139	0.2141	0.1454	0.1437	0.1441	0.1441	0.2232	0.2219	0.2224	0.2219
F-value	2.3693	5.6057	3.1096	4.4200	3.8608	9.8710	5.2518	9.9042	0.7262	0.4424	0.7333	0.2746

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
Specification 1 contains the following 13 duration dummies: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Specification 3 contains the following 5 duration dummies: 1-2 months (omitted), 3-4, 5-6, 7-12, 13 and more months. Specification 4 contains two continuous variables: duration in weeks and duration in weeks squared. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used.

Annex 6b) All ALMP participants with a LTU forecast

Dependent variable:		**Interviews per week**				**Interview Probability**				**Applications per week**		
Overall Effect ALMP	0.0386+	0.0305	0.0400+	0.0427+	0.0132+	0.0109+	0.0152*	0.0160*	0.2071*	0.1936*	0.1716+	0.1707+
(Dummy is 1 after ALMP announcement)	(0.0216)	(0.0222)	(0.0217)	(0.0226)	(0.0069)	(0.0066)	(0.0069)	(0.0068)	(0.1012)	(0.0962)	(0.0993)	(0.0997)
Duration												
Specification 1: 13 Dummies (standard)	yes	no	no	no	yes	no	no	no	yes	no	no	no
Specification 2: No time dummies	no	yes	no	no	no	yes	no	no	no	yes	no	no
Specification 3: 5 dummies	no	no	yes	no	no	no	yes	no	no	no	yes	no
Specification 4: 2 variables (duration, duration squared)	no	no	no	yes	no	no	no	yes	no	no	no	yes
Control variables (application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)												
Number of applications	3496	3496	3496	3496	9451	9451	9451	9451	3496	3496	3496	3496
Number of unemployed	166	166	166	166	166	166	166	166	166	166	166	166
Estimation (OLS with robust standard errors)												
R-squared	0.2748	0.2688	0.2714	0.2696	0.1864	0.1830	0.1851	0.1836	0.2244	0.2220	0.2230	0.2222
F-value	2.3576	1.5168	2.4851	1.4901	3.2209	2.9052	4.6508	3.7047	1.0121	1.5490	1.3668	1.0695

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
Specification 1 contains the following 13 duration dummies: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Specification 3 contains the following 5 duration dummies: 1-2 months (omitted), 3-4, 5-6, 7-12, 13 and more months. Specification 4 contains two continuous variables: duration in weeks and duration in weeks squared. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used.

Annex 6c) All ALMP participants without a LTU forecast

Dependent variable:	**Interviews per week**				**Interview Probability**				**Applications per week**			
Overall Effect ALMP	0.0150	-0.0371	-0.0150	-0.0201	0.0043	-0.0118	-0.0025	-0.0061	0.0280	-0.0516	-0.0238	-0.0050
(Dummy is 1 after ALMP announcement)	(0.0371)	(0.0384)	(0.0378)	(0.0387)	(0.0102)	(0.0094)	(0.0099)	(0.0100)	(0.1083)	(0.1102)	(0.1090)	(0.1081)
Duration												
Specification 1: 13 Dummies (standard)	yes	no	no	no	yes	no	no	no	yes	no	no	no
Specification 2: No time dummies	no	yes	no	no	no	yes	no	no	no	yes	no	no
Specification 3: 5 dummies	no	no	yes	no	no	no	yes	no	no	no	yes	no
Specification 4: 2 variables (duration, duration squared)	no	no	no	yes	no	no	no	yes	no	no	no	yes
Control variables (application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)												
Number of applications	2851	2851	2851	2851	7835	7835	7835	7835	2851	2851	2851	2851
Number of unemployed	162	162	162	162	162	162	162	162	162	162	162	162
Estimation (OLS with robust standard errors)												
R-squared	0.1825	0.1717	0.1755	0.1732	0.1178	0.1116	0.1142	0.1122	0.1806	0.1780	0.1788	0.1793
F-value	3.1401	5.7401	4.0171	4.0862	4.8861	9.2781	6.5348	8.9038	0.7125	0.3131	0.5672	0.9727

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
Specification 1 contains the following 13 duration dummies: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Specification 3 contains the following 5 duration dummies: 1-2 months (omitted), 3-4, 5-6, 7-12, 13 and more months. Specification 4 contains two continuous variables: duration in weeks and duration in weeks squared. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used.

Annex 7: Sensitivity test 4 – dropping outliers

Estimation without unemployed who show at any stage of their unemployment spells more than 15 applications a week or 5 interviews per week. Unemployed with an overall interview probability above 0.75 are not covered. If the unemployment spell is longer than 2 years, it is cut off after this point.

Dependent variable:	**Interviews per week**			**Interview Probability**			**Applications per week**		
Subsample: Forecast =	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**
Overall Effect ALMP	0.0245	0.0430*	0.0003	0.0056	0.0132+	-0.0054	0.1372+	0.2120*	0.0732
(Dummy is 1 after the announcement of the ALMP)	(0.0202)	(0.0215)	(0.0342)	(0.0061)	(0.0069)	(0.0100)	(0.0721)	(0.1018)	(0.1071)
Control variables (duration; application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)									
Number of applications	6428	3487	2785	17596	9432	7651	6428	3487	2785
Number of unemployed	331	165	157	331	165	157	331	165	157
Estimation (OLS with robust standard errors)									
R-squared	0.1866	0.2278	0.1595	0.1102	0.1429	0.0879	0.2160	0.2243	0.1867
F-value	2.1789	2.2664	2.8293	3.3079	3.2212	4.1352	0.7453	1.0210	0.6505

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used. The sample is split according to the duration forecast by the caseworker (LTU (long term unemployment): over 12 months).

Annex 8: Sensitivity test 5 – dropping personal applications with an unusual high success rate

Unemployed who report an overall interview probability above 0.9 for their personal applications are not covered.

Dependent variable:	**Interviews per week**			**Interview Probability**			**Applications per week**		
Subsample: Forecast =	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**
Overall Effect ALMP	0.0360+	0.0376+	0.0268	0.0118+	0.0121+	0.0068	0.0732	0.1691	0.0224
(Dummy is 1 after the announcement of the ALMP)	(0.0211)	(0.0218)	(0.0357)	(0.0062)	(0.0071)	(0.0103)	(0.0749)	(0.1044)	(0.1099)
Control variables (duration; application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)									
Number of applications	6263	3365	2734	17176	9060	7503	6263	3365	2734
Number of unemployed	319	158	152	319	158	152	319	158	152
Estimation (OLS with robust standard errors)									
R-squared	0.1834	0.2332	0.1510	0.1150	0.1500	0.0918	0.2263	0.2299	0.1807
F-value	2.3374	2.2277	3.1856	3.9109	3.1027	4.6701	0.7137	0.9894	0.7103

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used. The sample is split according to the duration forecast by the caseworker (LTU (long term unemployment): over 12 months).

Annex 9: Sensitivity test 6 – testing the no anticipation assumption

A dummy variable is added which switches to one in the period from one month before the ALMP announcement to the announcement.

Dependent variable:	Interviews per week			Interview Probability			Applications per week		
Subsample: Forecast =	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**	**All**	**LTU**	**Non-LTU**
Overall Effect ALMP	0.0496+	0.0414	0.0293	0.0194*	0.0164+	0.0123	0.1611+	0.2349+	0.0192
(Dummy is 1 after ALMP announcement)	(0.0275)	(0.0299)	(0.0482)	(0.0084)	(0.0099)	(0.0141)	(0.0972)	(0.1309)	(0.1527)
Placebo test	0.0283	0.0047	0.0196	0.0124	0.0050	0.0106	0.0962	0.0456	-0.0120
(Effect one month before announcement)	(0.0287)	(0.0299)	(0.0494)	(0.0075)	(0.0090)	(0.0124)	(0.0990)	(0.1264)	(0.1511)
Control variables (duration; application date relative to announcement; unemployment rate in occupation)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample (unemployed with ALMP)									
Number of applications	6518	3496	2851	17910	9451	7835	6518	3496	2851
Number of unemployed	338	166	162	338	166	162	338	166	162
Estimation (OLS with robust standard errors)									
R-squared	0.2173	0.2748	0.1825	0.1455	0.1864	0.1179	0.2234	0.2245	0.1806
F-value	2.3828	2.2276	3.0741	3.8311	3.0266	4.6669	0.7905	0.9499	0.6713

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The 13 duration dummies of control set 1 are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months. Unemployment rate in occupation is transformed by subtracting the median so the constant remains easy to interpret. All applications except the ones from the lay-off period and the last month of unemployment are used. The sample is split according to the duration forecast by the caseworker (LTU (long term unemployment): over 12 months).

Essay 2

The Effect of Unemployment Duration on Happiness and the Perceived Chances to Find a Job

Abstract

To gain new insights into the dynamics of unemployment, over three thousand responses by unemployed persons regarding their level of happiness and their perceived chances of finding a job within a month have been collected. Since the data set includes up to nine responses per unemployed, it allows using panel data regression methods and thereby cancelling out any unobserved individual heterogeneity. The results show that the Happiness Score displays little negative or positive development over the duration of unemployment. The self-assessed chances to find a job on the other hand increase despite the fact that objective chances rapidly fall over time. The study further shows that the application success has not much influence on the happiness of an unemployed person but that it does boost the perceived chances. Finally, most Active Labour Market Programs have a negative influence on both happiness and perceived chances.

1. Introduction

Ever since economists started to be interested in happiness as a research topic, the effect of unemployment on happiness has attracted much attention. This interest has not just be fuelled by the fact that unemployment has traditionally been a study subject of economics, but also because studies have repeatedly found large non-monetary costs generated by unemployment, costs in fact far larger than the estimated monetary effects through lost income. The main body of research has been devoted to comparing the happiness of the unemployed to the happiness of the employed. However, a few studies have focused on the unemployment spell itself and on the happiness dynamics over its duration. Quantitative research on this topic has been limited through the fact that most datasets only contain one measurement per person during the spell. Qualitative research on the other hand was able to observe the developments more closely, but couldn't quantify the impacts and therefore was not able to use more complex modelling.

Through the extensive data collected in one unemployment agency in Switzerland, it is now possible to look beyond the grainy analysis on duration effects conducted so far. This purpose-built database contains 3331 responses in total, with up to nine responses per unemployed persons. The responses were given by the unemployed once a month, either until the end of their unemployment spell or the end of the observational period. The panel structure of the dataset allows using panel data regression methods and thereby cancelling out any unobserved individual heterogeneity which might confound the estimation. As these observations stem from short and long term unemployed, it is possible to estimate the development over the whole duration of the unemployment spell.

Additionally, the database contains a new indicator: chances to find a job within the next 30 days, as predicted by the unemployed person him or herself. Apart from being an interesting indicator itself, data on the perceived chances allows observing how much the happiness level of the unemployed is determined through the self-assessed chances on the labour market. The dataset also contains data on the actual application success, on participations in ALMPs (Active Labour Market Programs) and sanctions in case of non-compliance with the rules of the unemployment insurance. Through this, several interesting determinants of happiness during unemployment can be tested.

The results show that there is a slight negative trend for the Happiness Score (which is measured on a scale from 0, not at all satisfied, to 10, very satisfied) over the duration of unemployment. Between the early stages of unemployment (i.e. the first two month) and late stages (i.e. after the twelfth month), the average unemployed experiences a -0.088 point drop in her or his Happiness Score. This drop is much smaller than the initial drop of happiness when a person becomes unemployed in Switzerland, which is - 1.6 points. This finding is similar to the one found in the two main studies conducted on the subject so far which have also not found any influence of duration, neither in a positive (a habituation effect) or negative way (rising frustration). Perceived chances to find a job within a month, also measured on a scale from 0 (no chance) to 10 (very good chances), gains an immense 1.382 points between early and late stages of unemployment. This is paradox as the actual chances fall heavily over time. A possible explanation could be that the increase is driven through a sense of deserving and impatience: After waiting for a long time, the unemployed person might increasingly feel that it is now her or his turn to get the job.

Being successful in the application process increases happiness, but just a little: The larger the number of interviews in the period before the measurement of the Happiness Score, the higher the score reported. The coefficients in these estimations are very small however and mostly not statistically significant. The level of search intensity (as measured through the number of applications written per week) has a negative effect on the level of happiness. On perceived chances on the other hand, the level of success has quite a large positive impact. The search intensity has almost no effect at all on the Perceived Chances Score.

ALMPs have in average a negative impact on both happiness and perceived chances. This negative impact takes place as soon as the ALMP is announced which indicates that the fact that they’re invited to participate in an ALMP is taken as a negative signal by the unemployed on their own employability. While the ALMP lasts, that impact on perceived chances is reversed. This could mean that the unemployed believes that the ALMP is going to have a positive impact on his or her chances. Once the ALMP has finished and the unemployed still doesn’t find a job however, the scores falls to levels lower than before the ALMP. In terms of sanctions, the influence on happiness and perceived chances is small and statistically insignificant.

Why is it important to study the level and development of happiness and perceived chances during unemployment? The findings of such research can give more insight on the non-monetary costs of unemployment and on the changes of mental health over the duration of unemployment. They might identify possible problematic periods during unemployment. This information can then be used by the public labour market administrations (and other interested organizations) to improve their consultation and placement services. Research on the dynamics of happiness and self-assessed chances over the duration of unemployment also promises new insights into why search intensity and success fluctuate over time, and thereby adds to the theoretical body of determinants of unemployment duration.

The paper is structured in the following way: In section 2, an overview over the previous literature and theory is given. Section 3 describes the two variables of interest, happiness and perceived chances, and the data used. In section 4, the development of the two variables over time is observed. Section 5 assesses how the application success affects happiness and perceived chances, and section 6 analyses how ALMPs and sanctions influence the two variables. Section 7 concludes.

2. Theory and related literature

In recent years, happiness economics has received a lot of attention, and the influence of unemployment on happiness has been one of the key topics. A good overview over this branch of literature is given by Clark (2006) and Carroll (2007). Studies have consistently found large non-monetary costs generated by unemployment, costs in fact far larger than the estimated monetary effects through lost income. The costs are not only large when expressed in monetary terms, but also when compared with other important blows of fate like divorce and widowhood (Clark and Oswald 2002a). For Switzerland, Frey and Stutzer (2002a) report that unemployed persons rate their happiness at an average score of 6.6 on a 10 point scale (10 representing complete satisfaction). Their employed compatriots showed a much higher average score of 8.2. Frey and Stutzer estimate that only a very small proportion of that effect is due to income loss. They show that the probability that a person reports a level of "complete satisfaction" drops by 21.5% when the labour market status is changed from employed to unemployed. If the monetary effects are held constant, that drop is still 20.6%, a mere 0.9 percentage point lower. This finding is very similar to estimations of the monetary and non-monetary costs of unemployment in other countries - apart from Italy and Spain, where there is a large loss of happiness through lower income (Frey and Stutzer 2002a). One would expect the monetary effect to depend primarily on the rules of the unemployment insurance. In Switzerland, these rules are comparatively generous: Unemployed received 70% to 80% of their former income for the duration of 18 months.

In terms of the simplest form of a labour supply model, the large non-monetary costs of unemployment are surprising: one would expect a positive impact of unemployment through more leisure time, once income is held constant. In explaining the costs of unemployment, the model is obviously too simple (Carroll 2007). Akerlof (1980) proposed a utility model which contains a reputation component. If unemployment is breaking social norms and leads to lower reputation, it results in a drop in utility. Indeed, Stutzer and Lalive (2004) showed that in Switzerland the reduction in life satisfaction through unemployment is larger if the norm to live off one's own income in the region is strong. Research on unemployment in Australia (Shields et al. 2008), Germany (Clarke et al. 2008), South Africa (Powdthavee 2006) and the United Kingdom (Shields and Wheatley Price 2005 and Clarke 2003) lends further support: The higher unemployment in an area, the smaller the effect on happiness when a person becomes unemployed (despite the fact that high unemployment actual decreases the chances to regain employment). In psychological studies too, much has been written about the negative link between unemployment and happiness. According to these studies, joblessness reduces an individual's perceptions of self-worth and nurtures feelings of lack of control and helplessness. As a result, unemployed persons are in worse mental and physical health condition than employed persons, and are more prone to depression and suicide (Frey and Stutzer 2002b). Unemployed also miss everything people like about their jobs apart from income; a provider of social relationships, identity in society and individual self-esteem (Winkelmann and Winkelmann 1997).

Because of the limited data on the subject, there has been only limited economic research on the dynamics of happiness over the unemployment spell. One of the two main studies stems from Winkelmann and Winkelmann (1997). These authors found on basis of German Socio-Economic Panel data that happiness is unrelated to unemployment duration: An unemployed person doesn't seem to be more or less affected by unemployment as time passes on. The authors conclude that there is no habituation effect over time. Clark (2006), using British Household Panel Survey, German Socio-Economic Panel and the European Community Household Panel, didn't find any effect of duration on happiness either. Both studies had to rely on datasets measuring happiness data once a year and therefore not able to observe how happiness levels changed between those intervals.

The main literature and theory on the effect of unemployment duration stems from psychological studies (see McKee-Ryan et al. (2005) and Paul (2005) for an overview). Two main models proposed in this literature are the cumulative stress model and the stage model. The cumulative stress model argues for a linear deterioration of mental health over the unemployment spell. Once unemployed, the stress level increases with time as frustration and despair set in with the continuous failure to get a job. Also, financial pressure increases as savings are used up (Jackson and Warr 1984). The more complex stage models on the other hand drop the assumption of a simple linear development over duration. They presume that there is a more complex development which can be described in stages which are roughly identical for all unemployed. Although the models differ in details, usually it is assumed that the mental health and happiness level are in relatively good shape at the beginning of unemployment, while there is still hope to find a job quickly. If the search for a job has failed in this initial stage, there is a large drop in the happiness level due to despair and frustration over the months that follow. After the crises, there is a final stage of adaptation at a happiness level which is higher than the low mark but lower than the level at the beginning of unemployment. Warr and Jackson (1987) distinguish between a constructive adaptation which is due to the creation of activities and relationships outside the job environment through which a regained control and sense of competence is developed, and the resigned adaptation which is based on lower aspirations. In contrast to the cumulative stress model, the stage models assume therefore a curvilinear relationship between unemployment duration and mental health (Paul 2005).

In a recent study by Knabe et al. (2009), the authors apply a new technique which measures the utility created by different activities. The authors find that generally, unemployed continue to long for employment and do not adapt their overall aspirations. Their joblessness continues to make them unhappy. However, hedonic adaptation takes place as the unemployed adjust their time-use: The unemployed are able to spend more time on activities they like to do (even though per time unit, they might experience less enjoyment for the same activity than an employed person). According to this study, the unemployed thereby experience overall a similar life satisfaction than employed persons.

Satisfaction and self-esteem were often treated as similar or at least closely related topics in the literature and have been looked at with the same models. Studies using an explicit self-esteem indicator like the Self-Esteem Inventory proposed by Rosenberg have shown results on the initial passage from employment to unemployed similar to the ones regarding the effect on life satisfaction: Unemployed have a lower level of self-esteem than employed persons (Waters and Moore 2002). As time progresses, one would expect the same downward trend for self-esteem as for happiness as theory predicts a deterioration of confidence when a job is not found over the initial period of unemployment. A study by Goldsmith et al. (1996) however found that unemployment duration has a positive effect on self-esteem. The authors describe this as “puzzling”, and think that one possible explanation is that as time progresses, the unemployed use more of their time for self-enrichment.

Perceived chances to find a job within a month, the indicator used in this study, are not the same as self-esteem. Rather, it is a combination of self-esteem, objective chances and the ability to assess these objective chances correctly. There is very little research on the development of these perceived chances over the duration of the unemployment spell. However, it has been shown that the objective chances to be invited to a job interview drop rapidly over time (see the first essay of the thesis). If self-esteem is diminished over time as well, one would expect a large drop of the perceived chances over the unemployment spell. If self-esteem increases as shown by Goldsmith, it could offset some of the downward trend of the objective chances, or could even reverse the trend. It’s further possible that the quality of the assessment of ones chances to find a job is quite low and that perceived and objective chances diverge. This could be a random deviation, but Kahneman and Lovallo (2000) show that the forecast of future outcomes are often anchored on scenarios of success rather than on past results. Many people are therefore overly optimistic. This could shift the reported perceived chances upward.

In the past, data on what people say rather than what people do has often been received with scepticism (Kahneman and Krueger 2006). Over time, such data has been more frequently used however, and lately, evidence has been gathered which shows that happy people don’t just report that they are happy but that the statement of happiness is accompanied by observables actions: Happy people smile more, and are described by family and friends as happy (Clark and Oswald 2002a).

One further objection against happiness research has been that different people understand the question used to measure happiness differently or attribute different ratings to the same level of happiness (as Clark and Oswald (2002b) put it, “your 5 is my 4”). Winkelmann and Winkelmann (1997) point out that these different ratings are closely related to the problem of unobserved individual specific effects. An estimation bias exists if the person has a different rating system (the authors call it anchoring) and that rating system is correlated with other observables which enter the model as independent variables. While this problem is difficult to solve with cross section data, it is relatively easy to fix using panel data: A dummy variable is entered for each individual (fixed effect) through which all unobserved individual differences can be excluded, as long as they are time-invariant over the course of the panel observation. Through these individual dummies, different individual anchoring can therefore be eliminated in the estimation (Clark and Oswald 2002b).

On the question of ordinal versus cardinal quality of the happiness variable, another discussed topic in literature, Frey and Stutzer (2000) write that the results are very similar, whether ordinal or cardinal treatments of satisfaction scores are used in microeconometric happiness functions. In this study, the score will be treated as a cardinal variable in order to use the more widely understood class of OLS regression methods.

3. Data

As in other countries, data on Swiss happiness is collected through the annual Swiss Household Panel. This panel includes unemployed persons, but is only surveyed once a year. There is no data on the perceived chances to find a job collected in a systematic way. Therefore the necessary data for this study had to be collected. This was done in one agency of the Swiss Unemployment Insurance in the city of Zurich, between 1st of July 2007 and 31st of March 2008. All unemployed persons registered at this agency during that time were asked to participate and to answer the question during their monthly counselling session, either until the end of their unemployment spell or until the end of the observational period, whichever came first. According to the case workers, most unemployed were happy to do so. Only 7.9 % refused to participate or were not able to answer because of language barriers. This led to a database containing data of 1247 unemployed persons, who filled out between 1 and 9 questionnaires. A total of 3331 responses to both questions were collected; the average number of responses per person is 2.7.

The two questions were asked at the beginning of the monthly counselling session of the unemployed person with his or her case worker. The interval of these sessions is not strictly on a monthly basis but instead depends on the need and urgency, as assessed by the case worker. A priori, one would expect that unemployed with good chances and good application behaviour (many applications and many job interviews) would be invited less often. If this expectation were to be true, it could have an impact on the balance in the sample and thereby distort the results. Fortunately, the data allows this to be tested: The dataset includes a duration forecast for each unemployed person. The forecast is an individual duration prediction recorded by the case worker at the start of the unemployment spell. The sample average (median value) is 38 days between measurements, with two modes at 28 days (local) and 35 days (global). For the group of the unemployed with a long term unemployment (LTU, i.e. a duration of more than 12 months) forecast, the median lies at 41 days. The group of unemployed with a Non-LTU forecast has a slightly lower median duration of 35 days between sessions (see Annex 1 for the distribution of the intervals). This means that the balance in the sample regarding observations from unemployed with low and high chances is kept to a large extent.

Much data stems from the beginning of the unemployment spells, as the unemployed get fewer as the duration of the spell progresses (Figure 1). The number of observations is relatively low after the 18th month, when most unemployed in Switzerland have used up their benefits. Some unemployed however can continue their spell for another few months (older unemployed and persons who participate in a work subsidy scheme). Of any month of the unemployment spell, the highest number of observations (i.e. an answer to one or both of the two questions) is achieved in the first month of unemployment, in which the number of observations reaches almost 700). None of the months of the unemployment spell reaches the maximum of 1247 observations (an observation for each of the 1247 unemployed), because the data is censored to the left and right through the start and end of the data collection period (e.g. for many unemployed the first month of unemployment was not observed because at the beginning of the observational period, they were already unemployed for more than a month). Further, not all members have the same number of observations as members leave the sample when they find a job (i.e. sample attrition). This "unbalancedness" of the panel could create a bias in the estimations, if the selection criterion is correlated to the error term. There is no reason however to believe that the fact that some people find a job earlier is correlated to the error term in the estimations on happiness and perceived chances, after controlling for the fixed effects (see Wooldridge 2009).

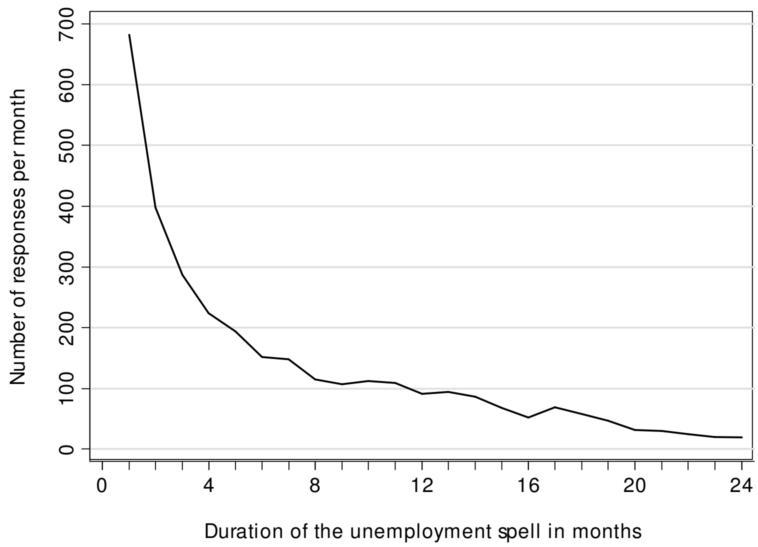


Figure 1: Number of observations recorded in the dataset, per month of the spell

Note: The figure shows the number of observation covered in each month. The duration is plotted until the 24th month, after which the entitlement time frame expires. A total number of 1247 unemployed are observed. Because the data is left and right censored through the beginning and end of the observation period, in no month a total of 1247 (i.e. one observation per person) is reached.

For most of the analysis, data of 1247 persons and their 3331 responses can be used. However, the sample size is decreased when analysing the influence of search intensity and search success on happiness and perceived chances. This is because the database only contains application information for 638 persons of the sample. Further, this sub-sample is a stratified sub-sample from the overall sample: It contains all unemployed with at least one participation in an Active Labour Market Program (ALMP), which make up a quarter of all unemployed registered. The sub-sample further contains a random selection of a third of the spells in which the unemployed did not attend such a program. The reason that the sample was taken with this stratification is that the data was also used to evaluate ALMPs (see the first essay of the thesis). Because of the stratification, data will be weighted in order to represent the proportions in the overall population, when (and only when) assessing the influence of the application behaviour and success (section 5).

In accordance to the standard happiness question used in surveys which contain such a question (such as the World Value Survey and different national Household Panels), the following question was used: In general, how satisfied are you with your life? The answers were given on a scale from 0 to 10, where 0 means "not at all satisfied" and 10 means "very satisfied". The terms happiness and life satisfaction are used as synonyms in this paper. A second question was then asked; According to your opinion, how good are your chances to find a job during the next month? One would expect that these self-assessed chances, or perceived chances as they are called in the reminder of this paper, are a combination of the objective chances, the ability to assess these objective chances correctly and a subjective component which could be interpreted as confidence or self-esteem. The answers were also given on a scale from 0 to 10, where 0 means "no chance" and 10 means "very good chances".

To get an overview, the distributions of the two variables of interest are shown in Figure 2 and 3. The average Happiness Score is 6.8 on a scale from 0 to 10, with a mode of 8. This is very similar to the value Frey and Stutzer (2002a) report for the whole of Switzerland, 6.6. There is a surprising amount of variation: The mode, 8, is only chosen by just over 20 % of all unemployed. Using the German Household Panel, Winkelmann and Winkelmann (1997) also found a global mode of 8 and a local mode at the middle response 5, reflecting a choice for unemployed who perceive themselves as neither particularly satisfied nor particularly dissatisfied. This local mode can also be found in the data from the Swiss agency.

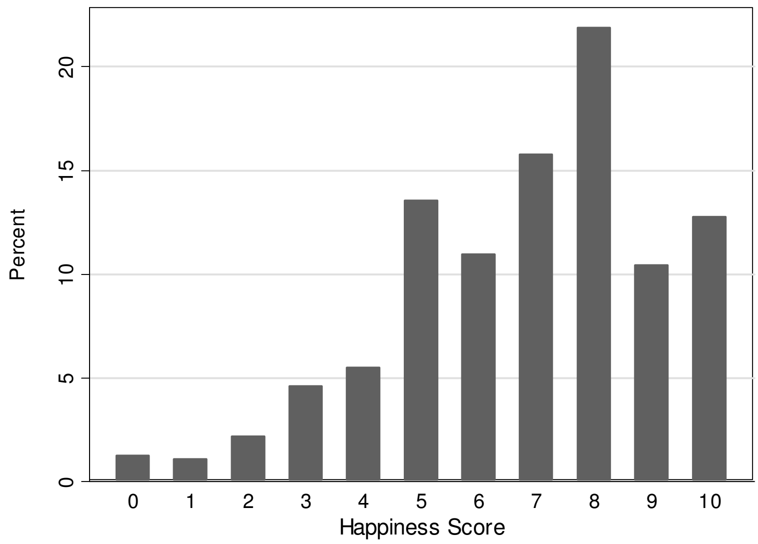


Figure 2: Distribution of the Happiness Score

Note: The figure shows the relative frequency with which the eleven possible answers were chosen. 0 means "not at all satisfied", 10 means "very satisfied". A total number of 3331 responses of 1247 unemployed are observed.

The self assessed chances to find a job within a month show an average of 6.2 measured on the same scale of 0 to 10. The distribution is even broader than the one of the happiness variable. The global mode lies at 5, which probably indicates an uncertainty how to judge one's own chances. The second largest (local) mode lies at 8 which indicates a large amount of optimism of finding a job soon.

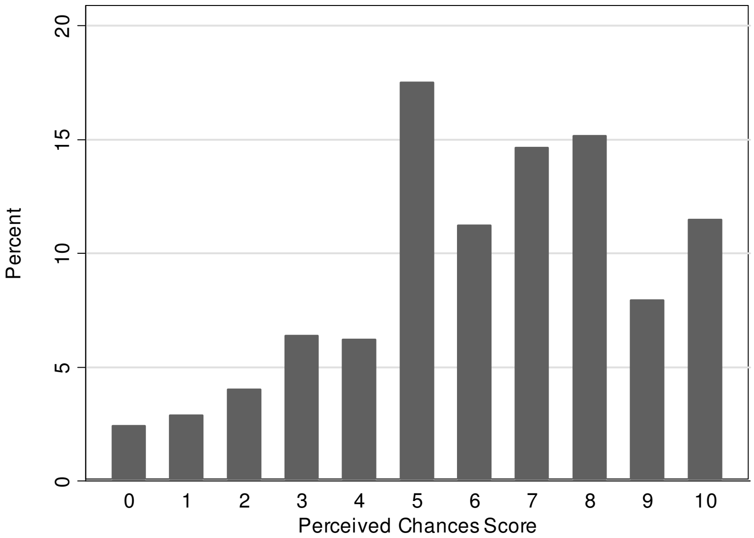


Figure 3: Distribution of Perceived Chances Score

Note: The figure shows the relative frequency with which the eleven possible answers were chosen. 0 means “no chance”, 10 means “very good chances”. A total number of 3331 responses of 1245 unemployed are observed.

One potential problem for the analysis could be a lack of ‘within’-variation in the data. If the overall variation would stem mainly from the variation between individuals, and hardly any variation from different answers from the same person (within variation), the estimation with fixed effects could not be performed in a reliable way. Table 1 shows however that although the between-variation is larger, there remains enough within-variation to work with (see Annex 2 for the summary statistics of the other variables). Further, one would expect that there is quite a large amount of random influences on the responses of the unemployed, determined through the many influences on how the person feels on the day or moment the questions are asked. While this makes the estimation less efficient, it does not bias it.

		Mean	Std. Dev.	Observations
Happiness Score	overall	6.8188	2.2753	N = 3331
	between		2.0785	n = 1247
	within		1.1263	T-bar = 2.6712
Perceived Chances Score	overall	6.2085	2.5507	N = 3331
	between		2.2542	n = 1245
	within		1.3374	T-bar = 2.6755

Table 1: Decomposition of the variance into between and within variation

Note: N is the number of responses, n the number of unemployed and T-bar the average number of responses per unemployed.

4. Effect of duration on happiness and perceived chances to find a job

To get an intuition of how the two variables of interest change over duration, the average per month is plotted from the beginning of the spell till the 24th month, after which the entitlement time frame in Switzerland expires (Figure 4). The figure shows that over the duration of the unemployment spell, there is a slow decline in both variables. The Happiness Score is relatively constant for most of the spell and only drops noticeably after the 15th month. Afterwards, the development of the Happiness Score is subject to higher fluctuation. This can be explained through the much lower number of observations at the end of the spell.

The Perceived Chances Score on the other hand starts on a lower level and then looses almost one point in the score till the 8th month. It then stabilises and even regains ground between the 15th and the 16th month. Over the rest of the spell, the Perceived Chances Score drops more than one point in the score. Again, there is high fluctuation in the score at the end of the spell due to few observations.

Figure 4: Development of happiness and perceived chances over the unemployment spell

Note: The figure shows the average score in a certain month. The duration is plotted until the 24th month, after which the entitlement time frame expires. For happiness, a total number of 3331 responses of 1245 unemployed are observed, for perceived chances 3331 responses of 1245 unemployed.

The descriptive analysis in Figure 4 shows the development of the sample average over the duration of the unemployment spell. The negative trend could stem either from changes in the values that are reported by the individual (the unemployed becomes unhappier and less confident over time) or from changes in the sample (unemployed with high levels of happiness and confidence leave the sample). Figure 5 shows that indeed, some of the changes stem from changes in the sample. The figure tracks the development of the sample average of the scores in month 1. In the first month, the sample is complete. Each month after the announcement, the sample looses members. The sample average of the month 1 values is mostly stable for life satisfaction. For perceived chances, the score falls steeply in the first few months but stabilises after month 4. The development can only be observed till the 6th month, because it's limited to unemployed who started their spell after the beginning of the observational period so that their score value in month 1 could be calculated. The observational number decreases quickly over time and for the subsample of persons who started their unemployment spell within the observational period, the number gets too low after the sixth month of the unemployment spell.

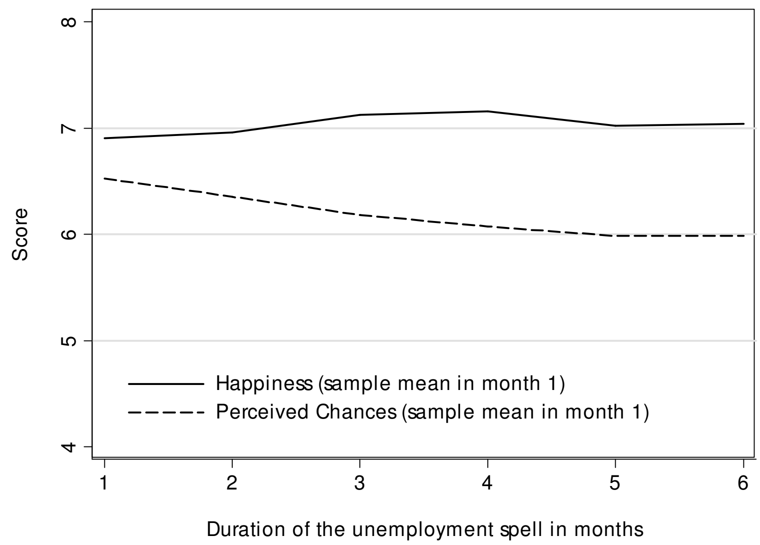


Figure 5: Sample attrition till the sixth month (development of sample mean of month 1 values)

Note: The figure shows the average value of the month 1 scores, and the development of the mean value as the sample decreases over time. The duration is plotted until the sixth month (the score in month 1 can only be calculated for unemployed who started their spell after the beginning of the observational period, July 2007, and the observational number decreases quickly over time – after month 6 it is low. For happiness, a total number of 1319 responses of 612 unemployed are observed, for perceived chances 1322 responses of 612 unemployed.

To measure the individual development, a simple regression model will be applied. The unit is a single response to a question of the survey. Because the number of responses to the happiness question is different to the responses regarding perceived chances, the observation numbers differ slightly between the estimations. As dependent variable, the model contains the Happiness Score of the person (or, in a separate model, the Perceived Chances Score), measured on a scale from 0 to 10. On the right side of the equation, four dummies are entered which indicate how much time, at the time of the score measurement, has passed since the start of the spell. The coefficient of a certain duration dummy indicates the impact of this period on the score as compared to the omitted dummy variable, the first two month. These dummies allow a flexible modelling of the effect of time. Overall, this is a very parsimonious model. However, this is desirable; by not adding further variables to the model, these variables are effectively allowed to vary over the month and all differences over time are captured by the duration dummies.

The first estimation is pooled (1st and 3rd column in Table 2). Because there are no other variables in the model, the values of the dummies correspond exactly to the development plotted in Figure 4 (apart from the fact that the periods in the model are aggregated into periods of two or more months). For the Happiness Score, there's a tendency of the coefficients to get larger (i.e. more negative) the later in the spell. This indicates a drop in the variables over time. Only the last of these coefficients is statistically significant on the 10 %-level. The Perceived Chances Score has less of a clear direction as time passes on: it first falls, then rises, then falls again. The coefficients are relatively small and statistically not significant.

Dependent variable:	**Happiness Score**		**Perceived Chances Score**	
Mean	6.819	6.819	6.209	6.209
Std. Dev.	2.275	2.275	2.551	2.551
Month 3 and 4	-0.122	-0.144	-0.133	0.357*
	(0.119)	(0.125)	(0.130)	(0.154)
Month 5 and 6	-0.043	0.059	-0.235	0.570*
	(0.162)	(0.193)	(0.167)	(0.230)
Month 7 to 12	-0.197	-0.055	-0.644**	0.942**
	(0.153)	(0.202)	(0.171)	(0.296)
Month 12 and later	-0.280+	-0.088	-0.850**	1.382**
	(0.158)	(0.300)	(0.185)	(0.380)
Fixed effects	no	yes	no	yes
Constant	6.945**	6.866**	6.575**	5.595**
	(0.080)	(0.118)	(0.084)	(0.160)
Sample				
Number of measurements	3331	3331	3331	3331
Number of unemployed	1247	1247	1245	1245
Estimation				
R-squared	0.0024	0.7554	0.0189	0.7302
F-value	1.0568	0.7276	6.6479	4.0344

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.

Table 2: The influence of duration on happiness and perceived chances

Clark (2003) presents some evidence that individuals who suffer most from unemployment might be the first ones to exit the unemployment insurance. If this happens, the calculated average happiness level would – other things being equal - be lower for short-term unemployed than for long-term unemployed, and the pooled results will be distorted (the issue is picked up in Figure 5, but due to the limited number of observations is only observed until the sixth month). Also, one often discussed issue in the happiness research literature is the anchoring issue: Different persons will report their score differently. Both issues can be addressed through estimation with fixed effects. The fixed effect models add a dummy for each unemployed, therefore excluding all time-invariant influences on the happiness or chances score. This estimation solely calculates the intra-person effect of duration and is not prone to changes in the composition of the sample or the individual anchoring.

The results in Table 2 (2nd column) show that the Happiness Score falls less if calculated with fixed effects. The difference between the first two months (early stages unemployment) and the period after the twelfth month (long term unemployment) is now only – 0.088 points, and is not statistically significant anymore. Although this result is highly surprising when compared to the theoretical body developed in psychology which predicts a much larger drop (see the theory section), it reflects what has been found using Household Panel data from Britain, Germany and Europe as a whole (Clarke 2006 and Winkelmann and Winkelmann 1997). Happiness seems to drop steeply when a person becomes unemployed (in Switzerland, the change is -1.6 points on the 10 point scale (as reported by Frey and Stutzer 2002a)), but the score is then relatively stable over the course of the unemployment spell.

For perceived chances, the results diverge even more, depending on whether one uses a pooled estimation or panel estimation with fixed effects (Table 2, 4th column). The results from the fixed effect estimation show a clear upward trend. This upward trend is very large; between the first two month of unemployment and the period after the twelfth month 1.382 points in the Perceived Chances Score are gained (this coefficient is significant on the 1 %-level). How can this large difference to the pooled results be interpreted? It seems that changes in the group composition are responsible for the downward trend as estimated by the pooled estimates: Unemployed who perceive their chances as low chances remain unemployed for longer (no causality implied). Once the group composition is held constant (through the inclusion of fixed effects), unemployed seem to get much more positive regarding their chances over time.

This finding is interesting as the perceived chances do not correspond with the actual probability of getting a job. The actual probability drops steeply over time, as employers get more wary as time progresses, taking the long unemployment duration as a signal for low employability (see the first essay of the thesis). Why do the unemployed believe that there chances are rising when they're actually falling? This might be due to a sense of deserving to get a job soon and patience running out: At the beginning, unemployed know that the search might take a while and that they have to be patient. With many applications written and duration progressing, many might start to think that their time has come to have a job offer and that this offer is going to happen soon or at least that it should happen soon. Another possible explanation is that an unemployed person has to explain to him or herself, and to the case worker of the unemployment insurance, that one is trying hard to find a job. The (perceived) possibility of finding soon a job provides the motivation to continue searching and the justification to keep receiving unemployment compensation payments.

Furthermore, it is quite difficult to track one's personal interview probability or even the average chances of success in the occupation or industry of the unemployed person. The upward trend of the score might therefore be explained partly by a lack of information (at least it explains why objective and perceived chances are not closely related). How do these results relate to the theories of the cumulative stress model and the stage model? At first glance the results do not seem to be supportive of either one, as the changes in the Happiness Score fluctuate around zero. However, it is not possible to discard the stage model as it is quite likely that the stages happen for each unemployed at different times down the track of the unemployment spell. The regression model calculates the average over these stages. What the data shows is that if there are stages, they are not happening at the same time for each unemployed.

As described in the theory section, there has been little research on perceived chances. It has been shown that the objective chances drop heavily over the spell (see the first essay). In regards to self esteem, it is less clear what to expect. Theory would lean towards a downward trend but Goldsmith et al. (1996) have found an upward trend over time. The prediction for perceived chances ranges therefore from negative duration impacts on perceived chances to positive ones if self-esteem would more than off-set the negative trend of the objective chances. Surprisingly, it seems to do exactly that. One likely explanation is a the perceived chances are not much shaped by the objective chances sense at all, and are instead influenced by a sense of deserving and an increasing lack of patience as the job search goes on.

Because the regression results are surprising, it's natural to question the validity of the model. In order to obtain further evidence, the results are replicated in an even simpler way. For each unemployed, the drop over time is calculated in a descriptive manner: First, the difference between the second period (month 3 and 4) and the first period (month 1 and 2) is calculated for both Happiness and Perceived Chances Score, for each individual. Then the average over these differences is calculated. This average difference should be similar to the coefficient obtained in the regression with fixed effects, because the individual component should be eliminated by calculating the difference for each individual. Similar differences can be calculated between later periods (month 5 and 6 and month 7 to 12) and the first period. It can not be calculated for the last period (month 12 and later), because there is no unemployed which has both data for this last period and the first period as the observational period only lasted for nine month: an unemployed in his or her second month at the beginning of the observational period would only have reached month 11 at the end of the observational period.

Difference to Month 1 and 2		**Happiness Score**	**Perceived Chances Score**
Month 3 and 4	Mean	-0.17	0.34
	Std. Dev.	1.63	2.10
	N (unemployed)	257	258
Month 5 and 6	Mean	-0.04	0.49
	Std. Dev.	2.23	2.32
	N (unemployed)	115	115
Month 7 to 12	Mean	-0.20	1.08
	Std. Dev.	1.70	2.99
	N (unemployed)	60	60
Month 12 and later	Mean	N/A	N/A
	Std. Dev.	N/A	N/A
	N (unemployed)	N/A	N/A

Notes: The difference to the first period (month 1 and 2) cannot be calculated for the last period (month 12 and later) as the observational period only lasted for nine month: an unemployed in his or her second month at the beginning of the observational period would have only reached month 11 at the end of the observational period.

Table 3: Development over time – descriptive differences

The results in Table 3 show that the calculated differences are very similar to the estimated coefficients in Table 2. This supports the finding that the Happiness Score indeed only shows little variation over the duration of the unemployment spell, while the Perceived Chances Score increases strongly over time.

Table 4 and 5 replicate the estimation shown in Table 2 for six different groups: women, men, Swiss, foreigners, unemployed under the age of 30 and unemployed over the age of 50. The mean values of the Happiness Score and the Perceived Chances Score per group are also displayed in the tables. One notices that women report a slightly higher Happiness Score then men and Swiss a higher one than foreigners. The largest deviation from the mean is found among unemployed over the age of 50, who report a mean score which is a third of a point lower than the average. In terms of perceived chances however, both men and foreigners report higher scores than women and Swiss respectively. While young people have the highest score of any of the six groups, people above the age of 50 have by far the lowest, more than a point below the mean.

Dependent variable: Happiness Score

	All	Women	Men	Swiss	Foreigners	Age < 30	Age > 50
Mean	6.819	6.902	6.742	6.868	6.761	6.996	6.495
Std. Dev.	2.275	2.264	2.284	2.187	2.376	2.335	2.424
Month 3 and 4	-0.144	-0.119	-0.166	-0.156	-0.126	-0.168	-0.530*
	(0.125)	(0.193)	(0.159)	(0.181)	(0.169)	(0.302)	(0.264)
Month 5 and 6	0.059	-0.017	0.142	0.195	-0.114	-0.037	-0.186
	(0.193)	(0.290)	(0.255)	(0.274)	(0.271)	(0.524)	(0.460)
Month 7 to 12	-0.055	-0.086	-0.020	-0.039	-0.080	-0.034	-0.383
	(0.202)	(0.295)	(0.277)	(0.252)	(0.335)	(0.685)	(0.381)
Month 12 and later	-0.088	-0.246	0.052	0.100	-0.365	1.104	-0.083
	(0.300)	(0.443)	(0.409)	(0.335)	(0.550)	(1.335)	(0.546)
Fixed effects	yes	yes	yes	yes	yes	yes	yes
Constant	6.866**	6.993**	6.745**	6.860**	6.900**	6.925**	6.689**
	(0.118)	(0.172)	(0.163)	(0.145)	(0.206)	(0.226)	(0.311)
Sample							
Number of measurements	3331	1600	1731	1808	1523	609	747
Number of unemployed	1247	598	649	709	538	292	233
Estimation							
R-squared	0.7554	0.7273	0.7807	0.7655	0.7460	0.7950	0.7420
F-value	0.7276	0.2297	0.6972	0.8474	0.1925	0.3306	1.5359

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.

Table 4: The influence of duration on happiness, group-wise estimation

In terms of the development over time, foreigners and women show the largest loss of happiness, at least if one compares the difference between early stages (month 1 and 2) and late stages (large term unemployment) as indicated by the coefficient for “Month 12 and later”. None of the coefficients are statistically significant however, apart from large coefficient for month 3 and 4 in the regression for the group above age 50). One notices a stark positive development for the unemployed below the age of 30, with a coefficient for “Month 12 and later” of over one point. This either indicates that this group has adapted their expectations and accepted the situation – or it could be due to a random change in a very small sample (note that the overall size of the group is 292, but only a small proportion of them become long term unemployed). The coefficient is not statistically significant.

Dependent variable: Perceived Chances Score

	All	Women	Men	Swiss	Foreigners	Age < 30	Age > 50
Mean	6.209	6.127	6.283	5.980	6.480	6.758	4.985
Std. Dev.	2.551	2.622	2.482	2.568	2.503	2.358	2.755
Month 3 and 4	0.357*	0.481*	0.237	0.354+	0.360	0.413	-0.265
	(0.154)	(0.243)	(0.193)	(0.212)	(0.223)	(0.423)	(0.364)
Month 5 and 6	0.570*	0.648*	0.492	0.572+	0.567	0.696	0.287
	(0.230)	(0.324)	(0.324)	(0.300)	(0.357)	(0.629)	(0.438)
Month 7 to 12	0.942**	1.247**	0.648+	0.980*	0.889*	1.388	-0.012
	(0.296)	(0.467)	(0.360)	(0.391)	(0.450)	(1.080)	(0.533)
Month 12 and later	1.382**	1.457*	1.280**	1.586**	1.087+	1.471	0.935
	(0.380)	(0.608)	(0.464)	(0.506)	(0.572)	(1.305)	(0.661)
Fixed effects	yes	yes	yes	yes	yes	yes	yes
Constant	5.595**	5.424**	5.765**	5.344**	5.921**	6.301**	4.637**
	(0.160)	(0.241)	(0.207)	(0.199)	(0.261)	(0.321)	(0.396)
Sample							
Number of measurements	3331	1595	1736	1810	1521	607	747
Number of unemployed	1245	596	649	710	535	292	233
Estimation							
R-squared	0.7302	0.6990	0.7630	0.7458	0.7052	0.7175	0.7646
F-value	4.0344	3.1264	1.2012	2.5918	1.5209	0.6527	0.6233

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.

Table 5: The influence of duration on perceived chances, group-wise estimation

In terms of the development of the Perceived Chances Score, the largest gains are found among the Swiss (1.586 points between the first two month and month 12 and later), while the smallest gain is made by the group of the unemployed aged 50 and above (0.935). All groups therefore show very strong positive gains.

5. Happiness, perceived chances and application performance

This section analysis the influence of a determinant one would expect to wield a very strong power over the happiness and perceived chances of the unemployed: the application success. Before looking at objective measures of success however, first the influence of the perceived chances on happiness will be analysed.

Figure 6 shows the scatter plot of the individual means of the Happiness and Perceived Chances Score. Each dot represents an unemployed person in the sample. While the cloud is widely dispersed over the whole field – practically all combinations exist – there seems to be a loose positive relation between the two scores: A happier person reports a higher Perceived Chances Score, and the other way round.

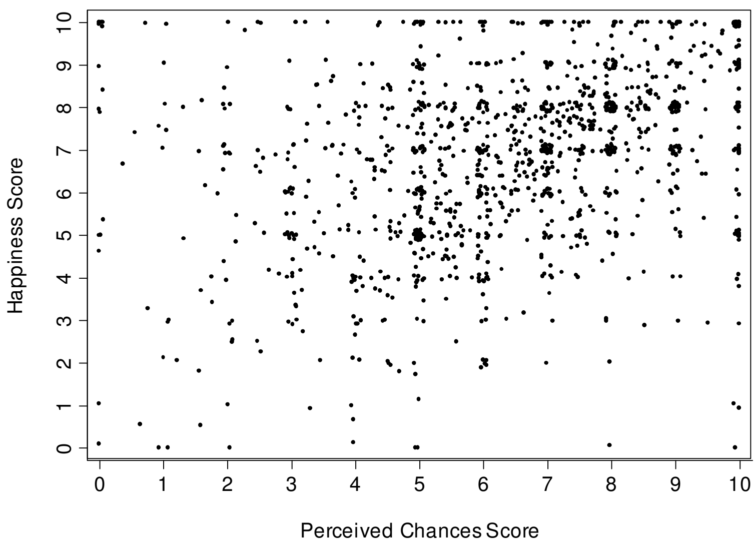


Figure 6: Interaction between happiness and self-perceived chances

Note: Each dot represents one unemployed with his or her mean value of Happiness Score and Perceived Chances Score. Some observations are overlapping. To make the number of observations and their distribution better visible, a small amount of jitter of the data points was introduced: Each dot is placed at a random location near its actual value. A total number of 1243 unemployed are observed.

This relationship is confirmed in the regression analysis (Table 6). The Perceived Chances Score has a strong influence on the Happiness Score. For each additional point on the Perceived Chances Score, the Happiness Score raises by 0.275 (significant on the 1 %-level). An additional point on the Happiness Score on the other hand increases the Perceived Chances Score by 0.387 (significant on the 1 %-level).

Dependent variable:	**Happiness Score**	**Perceived Chances Score**
Mean	6.822	6.208
Std. Dev.	2.272	2.547
Perceived Chances Score		
	0.275**	
	(0.035)	
Happiness Score		0.387**
		(0.043)
Duration (4 dummies, omitted: Month 1 and 2)	yes	yes
Fixed effects	yes	yes
Constant	5.302**	2.943**
	(0.234)	(0.310)
Sample		
Number of measurements	3321	3321
Number of unemployed	1243	1243
Estimation		
R-squared	0.7841	0.7583
F-value	1.4796	4.9062

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The four duration dummies are: Month 3 and 4, month 5 and 6, month 7 to 12 and month 12 and later

Table 6: Interaction between happiness and self-perceived chances

Annex 3 shows the results, when the estimation is run with the same variables, but a 1st difference approach is used rather than a fixed effects model. The general rule is that when the error term is serially uncorrelated, it is more efficient to use the fixed effect model. However, this assumption can be wrong. It is possible that the unobserved factors that change over the duration of the unemployment spell are actually serially correlated. If the error term follows a random walk (substantial positive serial correlation), then first differencing is the better approach as the difference of the error terms between periods are serially uncorrelated (Wooldridge 2009). Wooldridge suggests using both approaches and comparing the results. The table in Annex 3 shows that the results using the first differencing approach are very similar to the results with fixed effects.

One would assume that not just the self-assessed chances have a major influence on the happiness of an unemployed person, but that the actual application success might have an even stronger, more positive influence. To measure this influence, the number of applications written by the unemployed person and the number of job interview invitations received are entered as further determinants into the model. Three variations of both these two variables are tested: The number of job interviews (and applications) during the last month, the number of interviews (applications) during the month before last, and the cumulative number of interviews (applications) since the start of the unemployment spell up to the date of the Happiness and Perceived Chances Score measurement. Note that the dataset does not contain the actual date of the interview, it only contains the date of the application and a dummy variable indicating if the application led to an interview or not. One would expect the job interview to take place within the next 30 days and therefore the indicator "number of interviews last month" would be the most relevant one to measure the influence of application success. However, in case it might take longer for the average interview to take place or at least to leave its mark on the happiness and perceived chances of an unemployed, the variables will also be entered with a lag.

Generally for all three variations of the number of interviews, one would expect a positive relationship between application success and happiness and perceived chances to find a job within a month. For the number of applications (as a proxy for search intensity), the sign of the coefficient is less clear: The search intensity is directly influenced by the unemployed itself and one would expect an effect on the two scores, if any at all, mainly through lower utility through the search effort (negative influence on happiness) and a gratification or remorse effect for high or low search intensity over the previous month (positive influence on happiness). One would expect a positive influence of the search intensity on perceived chances as more applications should lead to more interviews. Finally, both interviews and applications are entered to see how what the influence of the interviews success is once search intensity is hold constant.

As discussed in the data section, only a random sub-sample of 638 unemployed (out of the total sample of 1247) can be used. Because this sample is stratified, weights will be used in the descriptive and analytical estimations of this section. In order to make sure that this sub-sample has similar characteristics and behaves the same way as the whole sample, the main results (from Table 2) are replicated for the sub-sample (see Annex 4). The results show that the sample and the sub-sample indeed behave in a very similar way.

Figure 7 shows the scatter plot of the relation of the number of interviews in the last month and the Happiness Score. Again, the point cloud is quite widely dispersed, but one could imagine traces of a weak positive relationship, as the cloud has an upward direction. However, this potential positive relationship is not confirmed in the regression analysis (Table 7). The results show that regarding the Happiness Score, the number of interviews in the last month has no influence whatsoever. The number of interviews in the month before last has a very small positive influence, and so does the cumulative number of interviews. The influence is very small indeed: In order to gain one point in the Happiness Score, one would have to add almost 100 interviews to the cumulative number of interviews since the start of unemployment. While the influence of search intensity is of a similar minuscule proportion, it seems more stable, resulting in high statistical significance levels (for number of applications last month and number of applications since the start of unemployment). Interestingly, the coefficients are negative: The higher the search intensity, the unhappier the unemployed. It seems that the negative influence of the search effort overrules any gratitude effect the average unemployed experiences through more applications. Of course, the number of applications is not completely exogenous; the unemployed person might write more applications because he or she realizes his or her difficulties in finding a job, which would both result in a higher number of applications and in unhappiness.

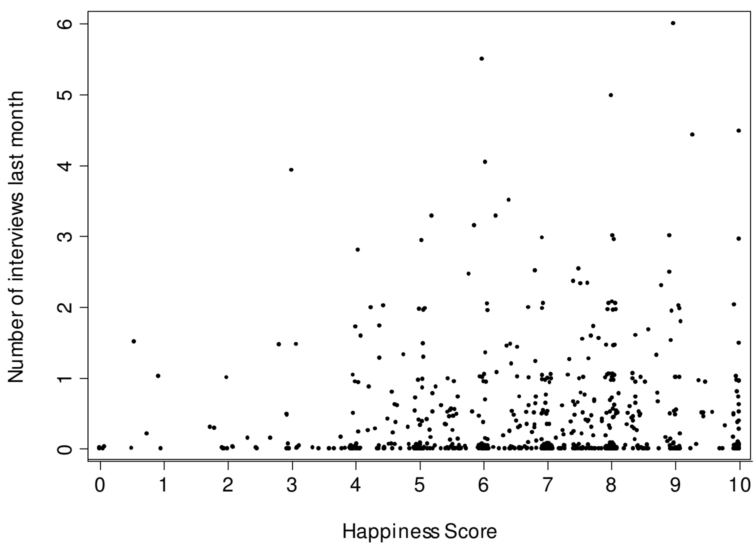


Figure 7: Happiness and application success

Note: Each dot represents one unemployed with his or her mean number of interviews in the month before measuring the Happiness Score, and the mean Happiness Score. Some observations are overlapping. To make the number of observations and their distribution better visible, a small amount of jitter of the data points was introduced: Each dot is placed at a random location near its actual value. A total number of 665 unemployed are observed.

Dependent variable: Happiness Score									
Mean	6.798	6.798	6.798	6.798	6.798	6.798	6.798	6.798	6.798
Std. Dev.	2.281	2.281	2.281	2.281	2.281	2.281	2.281	2.281	2.281
Number of interviews									
last month	-0.003						0.046		
	(0.043)						(0.046)		
the month before last		0.030						0.046	
		(0.045)						(0.048)	
since start unemployment			0.012						0.043*
			(0.019)						(0.019)
Number of applications									
last month				-0.030*			-0.034*		
				(0.012)			(0.013)		
the month before last					-0.008			-0.010	
					(0.012)			(0.013)	
since start unemployment						-0.011**			-0.013**
						(0.003)			(0.004)
Duration (4 dummies, omitted: Month 1 and 2)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	6.885**	6.888**	6.894**	7.024**	6.871**	6.728**	7.019**	6.872**	6.737**
	(0.150)	(0.147)	(0.150)	(0.149)	(0.147)	(0.150)	(0.150)	(0.147)	(0.151)
Sample									
Number of measurements	1987	1987	1987	1987	1987	1987	1987	1987	1987
Number of unemployed	665	665	665	665	665	665	665	665	665
Estimation									
R-squared	0.7455	0.7456	0.7455	0.7480	0.7456	0.7489	0.7482	0.7458	0.7499
F-value	1.0660	1.1357	1.1419	0.7014	0.7971	1.7770	0.7699	0.8347	2.4345

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The four duration dummies are: Month 1 and 2 (omitted), month 3 and 4, month 5 and 6, month 7 to 12 and month 12 and later

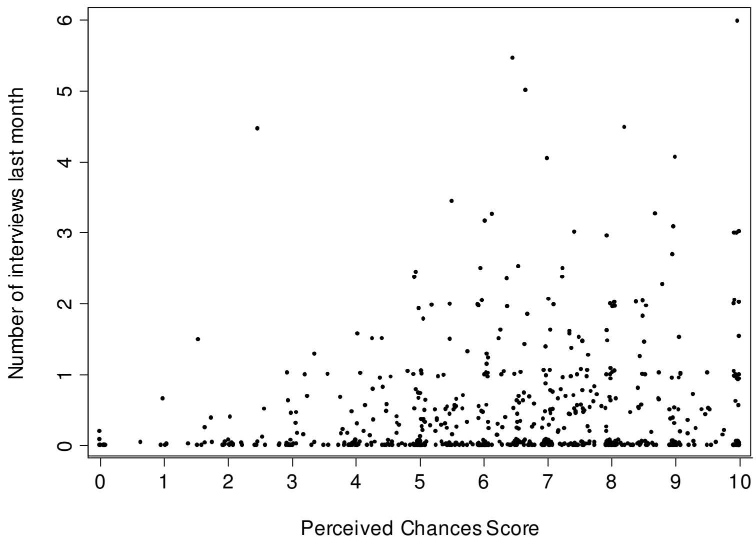
Table 7: The influence of search intensity and success on happiness

The coefficients for search intensity hardly change when both the number of applications and interviews are entered into the regression. The influence of application success however increases quite steeply once the search intensity is hold constant: It seems that success is appreciated once the disutility of the search effort is subtracted. Note however that the coefficients are still very small, i.e. the influence of both search intensity and success on happiness is marginal.

How about the influence of search intensity and success on the perceived chances to find a job within a month? The scatter plot (Figure 8) seems to reveal a positive influence of the number of interviews on the Perceived Chances Score. The regression analysis (Table 8) shows that while the number of interviews in the last month has only a minor influence, the number of interviews stemming from applications the month before last show a strong and statistically significant (on a 5 %-level) influence: Each additional interview increases the Perceived Chances Score by 0.223. The influence of the cumulative number of job interviews since the start of unemployment is a bit weaker but still strong: Each additional interview in the cumulative number of interviews increases the score by 0.130. It seems that the relationship is strongest when the interviews are still quite recent.

High search intensity also increases the Perceived Chances Score, but its relationship is a bit weaker than the one between the score and the number of interviews. The coefficient of the number of applications the month before last is 0.023 and statistically significant (on a 10 %-level). It means that by writing an extra 10 applications in that month, one get the same boost in self-esteem as one would receive by being invited to a single job interview (0.223). If one uses both the number of application and interviews in the regression, the influence of the search intensity decreases immensely however, while the influence of the number of interviews is quite stable. This indicates that the positive effect through writing more applications is mainly due to the fact that it increases the number of interviews, and not an intrinsic good feeling about one’s own chances just by having a high search intensity.

Figure 8: Perceived Chances and application success



Note: Each dot represents one unemployed with his or her mean number of interviews in the month before measuring the Perceived Chances Score, and the mean Perceived Chances Score. Some observations are overlapping. To make the number of observations and their distribution better visible, a small amount of jitter of the data points was introduced: Each dot is placed at a random location near its actual value. A total number of 664 unemployed are observed.

Dependent variable: Perceived Chances Score									
Mean	6.228	6.228	6.228	6.228	6.228	6.228	6.228	6.228	6.228
Std. Dev.	2.540	2.540	2.540	2.540	2.540	2.540	2.540	2.540	2.540
Number of interviews									
last month	0.015						0.008		
	(0.058)						(0.063)		
the month before last		0.223*						0.208*	
		(0.094)						(0.097)	
since start unemployment			0.130**						0.131**
			(0.032)						(0.035)
Number of applications									
last month				0.005			0.004		
				(0.014)			(0.015)		
the month before last					0.023+			0.010	
					(0.014)			(0.014)	
since start unemployment						0.006			-0.001
						(0.004)			(0.004)
Duration (4 dummies, omitted: Month 1 and 2)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	5.659**	5.697**	5.783**	5.643**	5.706**	5.748**	5.642**	5.713**	5.776**
	(0.175)	(0.181)	(0.177)	(0.179)	(0.185)	(0.194)	(0.177)	(0.185)	(0.185)
Sample									
Number of measurements	1988	1988	1988	1988	1988	1988	1988	1988	1988
Number of unemployed	664	664	664	664	664	664	664	664	664
Estimation									
R-squared	0.7185	0.7222	0.7263	0.7185	0.7194	0.7193	0.7185	0.7224	0.7263
F-value	2.5359	1.8501	0.9454	2.1384	1.3296	0.6644	1.8599	2.2567	3.2109

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
All applications except the ones from the lay-off period and the last month of unemployment (which are subject to different rules by the unemployment insurance) are used. The four duration dummies are: Month 3 and 4, month 5 and 6, month 7 to 12 and month 12 and later. Weights are used to compensate for stratified sample.

Table 8: The influence of search intensity and success on perceived chances

Using first differencing instead of a fixed effects model results in very similar results to the ones displayed in Table 7 and 8 (see Annex 5 and 6). The influence of the application success on happiness is even further weakened however. For the Perceived Chances Score, the only major difference is that the coefficient for the number of applications since the start of unemployment increases in size and becomes statistically significant (both when entered alone and when entered with the number of interviews).

6. Effect of ALMP participation and sanctions

In this model, events can now be entered to see what influence they wield over life satisfaction and perceived chances to find a job within a month. Two clearly identifiable events are the participation in an Active Labour Market Program (ALMP) and a sanction because an unemployed person has not fulfilled the requirements by the unemployment insurance. In the next section, it will be further analysed how the application success impacts on happiness and perceived chances.

ALMP are courses and programmes which aim to make reintegration of unemployed persons quicker and longer lasting. Sanctions are carried out if the unemployed doesn't fulfil the application requirements of the Swiss unemployment insurance. The sanctions are financial in nature as unemployed benefits are not paid out if a person is sanctioned (for a more in-depth description, see Lalive et al. 2005). In order to analyse the third research question, the effect of ALMP (Active Labour Market Program) participation and sanctions on happiness and self-esteem, the original regression model will be used, this time adding a dummy variable which will switch from 0 to 1 once an ALMP has been announced and a dummy variable which switches from 0 to 1 once a sanction has been carried out.

Of the 1247 unemployed used in the regressions on Happiness Score, 371 have participated in an ALMP, and 55 have been informed about a sanctioned (52 actually sanctioned). In the estimation of the Perceived Chances Score (1245 unemployed altogether), 370 have participated in an ALMP, 55 were informed about a sanction and 52 were sanctioned. Table 9 shows that the ALMP has a negative effect on the Happiness Score. However, this effect of -0.206 is not statistically significant from zero. The ALMP effect on perceived chances is also negative, but much larger at -0.407. This value is statistically significant on the 10 %-level and surprisingly large. In order to understand this effect, it helps to split the effect further up.

The next column splits the effect into three partial ALMP effects often discussed in literature; the threat effect, the lock-in effect and the skill-enhancement/signal effect (see the first essay of the thesis). The threat effect predicts that the search intensity rises after the announcement, as the unemployed is not keen on joining the ALMP. After the ALMP has started, theory predicts the occurrence of a second effect, the lock-in-effect. This effect happens if the ALMP is demanding and doesn't leave the unemployed enough time to write as many applications as they did before the ALMP started. Increasingly with the advancement of the ALMP, and especially once the ALMP has finished, the desired effects should set in, i.e. the skill enhancement and signal effect. All three partial effects discussed in literature are effects on the application behaviour. Nevertheless it is likely that these partial effects also leave traces on both happiness and perceived chances.

To check for these partial effects, a dummy is introduced which switches to 1 once the ALMP has been announced and then turns back to 0 once the ALMP has started. Additionally, a dummy switching to 1 while the unemployed participates in the ALMP, and a dummy switching to 1 after the ALMP has finished, are added to the model.

Dependent variable:	Happiness Score			Perceived Chances Score		
Mean	6.819	6.819	6.819	6.209	6.209	6.209
Std. Dev.	2.275	2.275	2.275	2.551	2.551	2.551
Overall ALMP effect	-0.206			-0.407+		
(Dummy is 1 after ALMP announcement)	(0.212)			(0.235)		
Partial effects						
Threat Effect		-0.184			-0.314	
(Dummy is 1 between announcement and start)		(0.233)			(0.250)	
Lock-in Effect		-0.013			0.043	
(Dummy is 1 between start and end)		(0.251)			(0.282)	
Skill enhancement and signal effect		-0.380			-0.549+	
(Dummy is 1 after ALMP ends)		(0.247)			(0.311)	
ALMP Type						
Basic course (167 participants)			-0.490			-0.637
			(0.320)			(0.412)
Personality oriented course (50 participants)			-0.019			-0.183
			(0.534)			(0.395)
Basic qualifications course (20 participants)			-0.011			-0.088
			(0.672)			(1.511)
Language course (23 participants)			0.637			0.522
			(0.594)			(0.376)
Other course (36 participants)			0.341			0.054
			(0.565)			(0.465)
Employment programme (78 participants)			-0.387			-0.704
			(0.450)			(0.468)
Duration (4 dummies, omitted: Month 1 and 2)	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes
Constant	6.882**	6.866**	6.883**	5.625**	5.599**	5.626**
	(0.120)	(0.123)	(0.118)	(0.160)	(0.161)	(0.159)
Sample						
Number of measurements	3331	3331	3331	3331	3331	3331
Number of unemployed	1247	1247	1247	1245	1245	1245
Estimation						
R-squared	0.7556	0.7560	0.7564	0.7309	0.7312	0.7316
F-value	0.7586	0.9203	0.7839	4.0313	2.8761	2.6933

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The four duration dummies are: Month 3 and 4, month 5 and 6, month 7 to 12 and month 12 and later.

Table 9: The influence of Active Labour Market Programs on happiness and perceived chances

The results in Table 9 show that all three effects are negative when regressing on Happiness Score, with the largest one being after the ALMP and the smallest one during the ALMP. All partial effects are insignificant. Similarly, for perceived chances the largest negative effect happens after the ALMP has finished (at -0.549, this coefficient is large and significant on a 10 %-level). During the ALMP however, the effect is practically zero. A possible explanation is that the unemployed believe that the skill-enhancing nature of the course is effective and that the ALMP increases their chances; and that the unemployed therefore readapt their chances to the initial level before the ALMP announcement. They are later disillusioned (as indicated through the negative coefficient after the ALMP) if they don't find a job soon after it has finished. Alternatively, the positive effect might be explained by the effect of seeing unemployed with even worse chances (lower language skills or the like) in the course. Through this, the unemployed might judge their employability relative to other unemployed instead of comparing it to the employability of the employed. Interestingly, the announcement of the ALMP has a strong negative effect itself. The announcement by the case worker might be taken as a signal by the unemployed that her or his chances on the labour market are quite low, and maybe lower than anticipated.

It is important to note that a negative effect is not necessarily a bad characteristic for an ALMP as it could entail adjusting unrealistic expectations. Indeed, some support for this thesis can be gathered from the third column in Table 9, which shows the effect by different types of ALMP (each type has its own dummy variable which switches to 1 after that particular type of ALMP has been announced). There seems to be a large negative effect of the Basic Course, which is – besides other goals - intended to address unrealistic expectations, on the Perceived Chances Score. The Basic Course also has quite a strong negative impact on the Happiness Score of its participants. Two more courses are worth mentioning: Language courses have a strong and positive impact on the happiness level and the Perceived Chances Score of its participants (both effects are insignificant however, due to the small number of observations). Employment programmes have a large negative effect on the perceived chances. These programmes are often used by the case workers quite late in the unemployment spell as an ALMP of last resort. This might be observed by the unemployed who interpret their participation as a negative signal on their own employability.

Summing up, ALMPs have a negative impact on both happiness and perceived chances in average. This effect is particularly strong for the Basic Course and the employment programmes, while language courses show a positive effect. These estimates do not give away the reasons for the negative impact, but possible interpretations are that the ALMP are taken as a negative signal by the unemployed on their own employability. While the ALMP lasts, there is a positive impact on perceived chances, which can be interpreted that the unemployed trust the positive impact of the ALMP. Once the ALMP has finished and the unemployed still didn’t find a job however, the scores are lower than before the ALMP.

Next, the influence of sanctions on happiness and perceived chances is examined. The first column of Table 10 shows the effect of the sanction carried out (the dummy switches to one once the person was sanctioned). It is very small on both the Happiness Score and the perceived chances, and statistically insignificant. A possible explanation could be that the effect does not happen when the financial sanction is carried out but instead when the unemployed is informed that a sanction has been filed for by the case worker (the sanction is not carried out by the case worker but instead by another department of the Office of Labour and Economy). This effect, shown in the second column, results in similarly small coefficients. Looking at the signs, one can conclude that sanctions has not influence on the happiness of the sanctioned unemployed, but that the sanctioned unemployed correct their perceived chances upwards (why that might be is unclear). However, the coefficients should not be over-interpreted: the coefficients are small and statistically insignificant. A potential explanation for this small influence might be that the unemployed already expected to be sanctioned (even before they were informed) and that they therefore already incorporated the change in their Happiness and Perceived Chances Score.

Dependent variable:	Happiness Score		Perceived Chances Score	
Mean	-0.039	-0.039	0.025	0.025
Std. Dev.	2.024	2.024	2.411	2.411
Sanction effect	-0.041		0.136	
(Dummy is 1 after sanction has been carried out)	(0.199)		(0.235)	
Sanction filed effect		0.051		0.113
(Dummy is 1 after sanction has been filed)		(0.197)		(0.229)
Duration (4 dummies, omitted: Month 1 and 2)	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes
Constant	6.864**	6.868**	5.602**	5.600**
	(0.118)	(0.118)	(0.160)	(0.160)
Sample				
Number of measurements	3331	3331	3331	3331
Number of unemployed	1247	1247	1245	1245
Estimation				
R-squared	0.7554	0.7554	0.7303	0.7302
F-value	0.5634	0.5535	3.0377	3.0224

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The four duration dummies are: Month 3 and 4, month 5 and 6, month 7 to 12 and month 12 and later.

Table 10: The influence of sanctions on happiness and perceived chances

When recalculating the models in Table 9 and 10 with a first differencing estimation, one notices that the ALMP effect on happiness and perceived chances grow in size (see Annex 7 and 8). The effect on happiness increases from -0.206 to -0.307 and the effect on perceived chances from -0.407 to -0.448. Latter is now statistically significant on a 1 %-level. Similarly, the partial effects and the effects of the different types of ALMP grow stronger and some become statistically significant. In terms of sanctions, the coefficients change their size a bit but stay small and statistically insignificant.

7. Conclusion

To conduct this study, 3331 responses from the unemployed on their happiness level and perceived chances to find a job during the next month have been collected. This customized data set allows calculating the influences of unemployment duration on happiness and perceived chances during the unemployment spell in a more detailed way that other studies have been able to do. Insights into the dynamics over the unemployment spell are important in order to maximize the effectiveness of the interventions by the case workers and the instruments used by the unemployment insurance.

The analysis of the collected data shows that the Happiness Score does not change considerably over the duration of unemployment. Perceived chances on the other hand grow strongly as time passes. This interesting finding might be explained by a sense of deserving and impatience: After waiting for such a long time, an unemployed person might feel increasingly that it is now her or his turn to get the job. This is a phenomenon which should be analysed further. This feeling of overconfidence (relative to the actual objective chances) might have a negative impact on the search intensity and create a too narrow search field. On the other hand, it might be a positive occurrence if it motivates unemployed persons who were unmotivated through the awareness of their low chances. It might be a case of some people gaining from a (unrealistic) boost of their self confidence, and others loosing.

The Happiness Score is only influenced in a very small way by the search intensity (measured as the number of applications per month). The relation is negative: the more applications she or he writes, the unhappier the unemployed person. The search success (measured as the number of interviews per month) has a small positive influence on happiness. The Perceived Chances Score on the other hand is influenced strongly and positively by the number of interviews. Finally, two major institutional events during an unemployment spell, a participation in an Active Labour Market Program (ALMP) and sanctions being carried out due to non-compliance, were analysed. The results show that on average, ALMP have a negative impact on both happiness and perceived chances, while sanctions only show a minor positive effect on the Perceived Chances Score.

The results show that happiness and perceived chances are a complex topic. While this study has exposed some of the influences on happiness and perceived chances, there is much to be learned. While there is a large literature body on qualitative research on happiness and self-esteem during unemployment, the volume of quantitative data and therefore studies is still slim. One interesting development is the gathering of quantitative data on a very detailed level, for example through the Day Reconstruction Method proposed by Kahneman and Krueger (2006) which allows the measurement of the satisfaction of different types of single activities. Because the gathering of this kind of data is very resource intensive and therefore does not allow covering many persons, it will also be necessary to continue to gather more simple data on as many persons as possible. The gap in quantitative research on the dynamics over the unemployment spell should be filled. This would allow researchers, government agencies and organizations in the unemployment sector to learn more about unemployment and improving their services.

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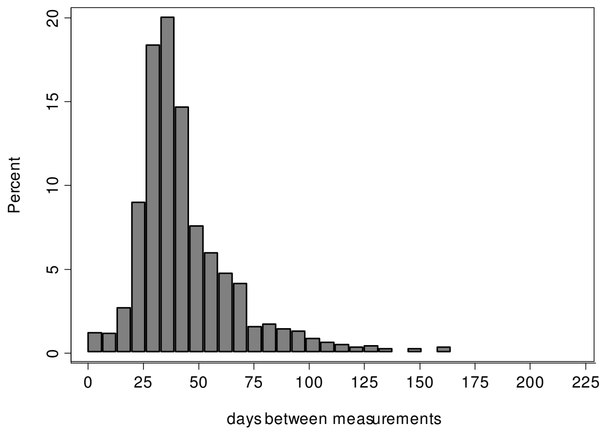
Annex

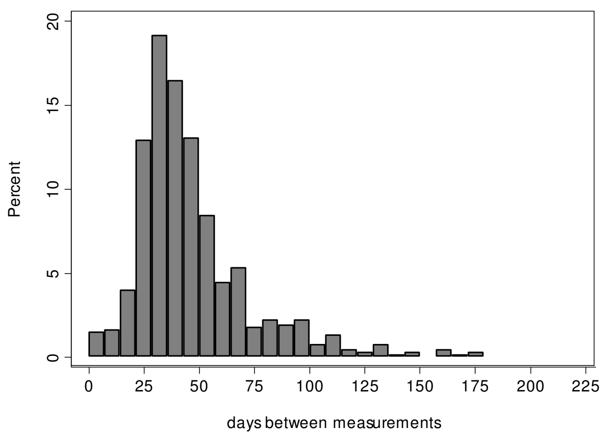
Annex 1: Distribution of the intervals between measurements

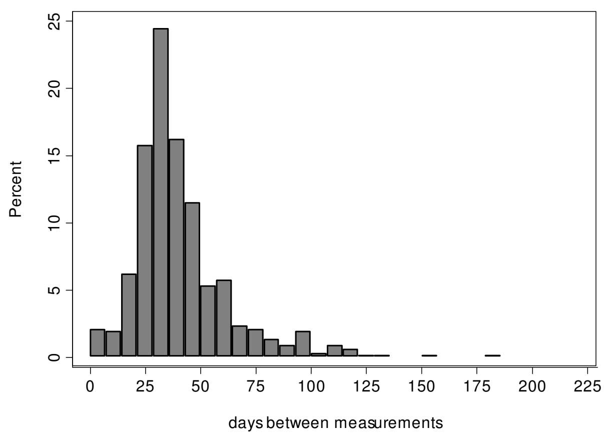
All unemployed



Note: Only observations with more than one measurement are taken into account. 847 unemployed with 2981 responses are observed. The median value of “days between measurements” is 38 days.

Unemployed with LTU forecast (left) and with Non-LTU forecast (right)





Note: Only observations with more than one measurement and a duration forecast by the case worker are taken into account. The sample is split according to the duration forecast by the caseworker (LTU (long term unemployment): over 12 months). 309 unemployed with LTU forecast are observed, with 983 responses. 281 unemployed with Non-LTU forecast are observed, with 960 responses. The median value of “days between measurements” is 41 days for unemployed with a LTU forecast, and 35 days for unemployed with a Non-LTU forecast. The number of observations from unemployed with a LTU and a Non-LTU forecast is smaller than the total number of observations as the unemployment duration forecast is only available for the sub-sample of unemployed who have data on the application behaviour (see section 3).

Annex 2: Summary statistics of main variables

	Mean	Std. Dev.
Happiness	6.819	2.275
Self-assessed chances	6.209	2.551
Applications per month	8.024	5.418
Interviews per month	0.477	1.197

	Number of unemployed	Proportion of total number
Total	1247	
Women	598	0.480
Foreigners	538	0.431
Age < 30	292	0.234
Age > 50	233	0.187
Unemployed with a		
- ALMP participation	371	0.298
- Sanction (informed)	55	0.044
- Sanction (carried out)	52	0.042

Annex 3: Interaction between happiness and self-perceived chances (first difference estimation)

Dependent variable:	**Happiness Score**	**Perceived Chances Score**
Mean	-0.039	0.025
Std. Dev.	2.024	2.411
Perceived Chances Score	0.285**	
	(0.304)	
Happiness Score		0.405**
		(0.037)
Duration (4 dummies, omitted: Month 1 and 2)	yes	yes
Constant	-0.054*	0.044
	(0.026)	(0.032)
Sample		
Number of measurements	2072	2072
Number of unemployed	836	836
Estimation		
R-squared	0.1160	0.1283
F-value	19.1188	29.1458

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The four duration dummies are: Month 3 and 4, month 5 and 6, month 7 to 12 and month 12 and later.

Annex 4: The influence of duration on happiness and perceived chances (Replicated results for the sub-sample with application data)

Dependent variable:	**Happiness Score**		**Perceived Chances Score**	
Mean	6.819	6.798	6.209	6.228
Std. Dev.	2.275	2.281	2.551	2.540
Month 3 and 4	-0.144	-0.283+	0.357*	0.235
	(0.125)	(0.164)	(0.154)	(0.193)
Month 5 and 6	0.059	-0.097	0.570*	0.294
	(0.193)	(0.253)	(0.230)	(0.243)
Month 7 to 12	-0.055	0.030	0.942**	0.856*
	(0.202)	(0.280)	(0.296)	(0.343)
Month 12 and later	-0.088	-0.175	1.382**	1.625**
	(0.300)	(0.390)	(0.380)	(0.520)
Fixed effects	yes	yes	yes	yes
Constant	6.866**	6.884**	5.595**	5.665**
	(0.118)	(0.147)	(0.160)	(0.181)
Sample				
Number of measurements	3331	1987	3331	1988
Number of unemployed	1247	665	1245	664
Estimation				
OLS	yes	yes	yes	yes
R-squared	0.7554	0.7455	0.7302	0.7185
F-value	0.7276	0.7455	4.0344	3.3259

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.

Annex 5: Regression of application performance on happiness (first difference estimation)

Dependent variable: Happiness Score									
Mean	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
Std. Dev.	2.087	2.087	2.087	2.087	2.087	2.087	2.087	2.087	2.087
Number of interviews									
last month	-0.004						0.051		
	(0.043)						(0.046)		
the month before last		-0.004						0.010	
		(0.052)						(0.055)	
since start unemployment			-0.002						0.030
			(0.023)						(0.025)
Number of applications									
last month				-0.036**			-0.040**		
				(0.013)			(0.014)		
the month before last					-0.009			-0.010	
					(0.014)			(0.014)	
since start unemployment						-0.011**			-0.012**
						(0.004)			(0.004)
Duration (4 dummies, omitted: Month 1 and 2)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	0.019	0.020	0.019	0.014	0.019	0.012	0.017	0.019	0.016
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Sample									
Number of measurements	1319	1319	1319	1319	1319	1319	1319	1319	1319
Number of unemployed	496	496	496	496	496	496	496	496	496
Estimation									
R-squared	0.0106	0.0106	0.0106	0.0239	0.0113	0.0231	0.0251	0.0114	0.0246
F-value	1.8360	1.8369	1.8374	3.1347	1.8216	3.2288	2.7213	1.5176	2.7488

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The four duration dummies are: Month 3 and 4, month 5 and 6, month 7 to 12 and month 12 and later.

Annex 6: Regression of application performance on perceived chances (first difference estimation)

Dependent variable: Perceived Chances Score									
Mean	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
Std. Dev.	2.437	2.437	2.437	2.437	2.437	2.437	2.437	2.437	2.437
Number of interviews									
last month	0.001						-0.008		
	(0.058)						(0.061)		
the month before last		0.209*						0.188*	
		(0.090)						(0.094)	
since start unemployment			0.119**						0.102**
			(0.031)						(0.033)
Number of applications									
last month				0.006			0.007		
				(0.015)			(0.015)		
the month before last					0.026+			0.014	
					(0.014)			(0.015)	
since start unemployment						0.011**			0.006+
						(0.003)			(0.004)
Duration (4 dummies, omitted: Month 1 and 2)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	0.071	0.073	0.088+	0.072	0.074	0.078+	0.072	0.074	0.090+
	(0.047)	(0.046)	(0.046)	(0.047)	(0.047)	(0.047)	(0.047)	(0.046)	(0.046)
Sample									
Number of measurements	1323	1323	1323	1323	1323	1323	1323	1323	1323
Number of unemployed	498	498	498	498	498	498	498	498	498
Estimation									
R-squared	0.0158	0.0281	0.0349	0.0161	0.0202	0.0253	0.0161	0.0293	0.0376
F-value	2.4119	3.6187	4.8237	2.7716	3.3391	4.3657	2.3067	3.3717	4.5053

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The four duration dummies are: Month 3 and 4, month 5 and 6, month 7 to 12 and month 12 and later.

Annex 7: Regression of ALMP participation on happiness and perceived chances (first difference estimation)

Dependent variable:	Happiness Score			Perceived Chances Score		
Mean	-0.039	-0.039	-0.039	0.025	0.025	0.025
Std. Dev.	2.024	2.024	2.024	2.411	2.411	2.411
Overall ALMP effect	-0.307			-0.448*		
(Dummy is 1 after ALMP announcement)	(0.194)			(0.209)		
Partial effects						
Threat Effect		-0.227			-0.263	
(Dummy is 1 between announcement and start)		(0.215)			(0.220)	
Lock-in Effect		0.069			0.184	
(Dummy is 1 between start and end)		(0.250)			(0.220)	
Skill enhancement and signal effect		-0.620*			-0.789**	
(Dummy is 1 after ALMP ends)		(0.243)			(0.265)	
ALMP Type						
Basic course (167 participants)			-0.574*			-0.777*
			(0.265)			(0.375)
Personality oriented course (50 participants)			-0.124			0.020
			(0.382)			(0.449)
Basic qualifications course (20 participants)			-0.109			0.375
			(0.697)			(1.088)
Language course (23 participants)			0.552			0.569+
			(0.619)			(0.342)
Other course (36 participants)			0.234			-0.108
			(0.386)			(0.322)
Employment programme (78 participants)			-0.486			-0.789*
			(0.505)			(0.363)
Duration (4 dummies, omitted: Month 1 and 2)	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes
Constant	-0.021	-0.021	-0.024	0.051	0.050	0.046
	(0.027)	(0.027)	(0.027)	(0.033)	(0.034)	(0.033)
Sample						
Number of measurements	2080	2080	2080	2082	2082	2082
Number of unemployed	838	838	838	840	840	840
Estimation						
R-squared	0.0052	0.0094	0.0083	0.0225	0.0264	0.0268
F-value	1.3358	1.9769	1.1776	5.4753	4.9031	4.0246

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The four duration dummies are: Month 3 and 4, month 5 and 6, month 7 to 12 and month 12 and later.

Annex 8: Regression of sanctions on happiness and perceived chances (first difference estimation)

Dependent variable:	Happiness Score		Perceived Chances Score	
Mean	-0.039	-0.039	0.025	0.025
Std. Dev.	2.024	2.024	2.411	2.411
Sanction effect	0.052		0.109	
(Dummy is 1 after sanction has been carried out)	(0.181)		(0.208)	
Sanction filed effect		0.175		0.054
(Dummy is 1 after sanction has been filed)		(0.176)		(0.210)
Duration (4 dummies, omitted: Month 1 and 2)	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes
Constant	-0.023	-0.022	0.048	0.048
	(0.027)	(0.027)	(0.033)	(0.033)
Sample				
Number of measurements	2080	2080	2082	2082
Number of unemployed	838	838	840	840
Estimation				
R-squared	0.0032	0.0038	0.0194	0.0193
F-value	0.8107	0.9926	4.3336	4.3055

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The four duration dummies are: Month 3 and 4, month 5 and 6, month 7 to 12 and month 12 and later.

Essay 3

An Opening Door?

Surprising Evidence that Foreigners Have Above-Average Chances to Find a Job When Controlling for the Quality of the Match Between the Job-seeker and the Requirements of the Job advertisement

Abstract

In order to identify the discriminatory component of divergent labour market outcomes it is necessary to determine how much of the divergence can be explained through different productivity, job choices and other influences. Because of usually high levels of unobserved heterogeneity in the data, this is often a difficult challenge for discrimination research. A new dataset on unemployed job seekers allows considerably reducing this unobserved heterogeneity by including data on the quality of the match between the job seeker and the requirements of the job advertisement, the application behaviour and the occupational distribution. Especially the match to the language requirements (as part of the matching quality) has a large influence on the estimation. The results show that foreigners have above average chances to be invited to a job interview, once one includes controls for the matching quality, the application behaviour and the occupational distribution.

1. Introduction

Discrimination has not just been a hotly debated topic in political discussions, but ever since Gary Becker sparked their interest in the 1950's it has also been an important theoretical and empirical issue for economists. In the economic literature on discrimination, one of the most important issues has always been the question why discrimination can persist in a competitive market. Wouldn't non-discriminating employers make a premium by employing members of the underpaid discriminated group and eventually drive discriminating employers out of the market? One strain of literature has argued that the differences in labour market outcomes like wages are not signs of discrimination but instead can be explained through differences in productivity (lower education or a different job choice for example). This argument has made unobserved heterogeneity a core topic of the debate on discrimination: If the relevant differences between groups and their members are not captured in the data, the estimations might over- or underestimate the part of the difference in the labour market outcome between the two groups which can be interpreted as discrimination.

This study is able to reduce the extent of unobserved heterogeneity by approaching the ultimately unobservable productivity from another angle; through the matching of the characteristics of the job seeker with the requirements mentioned in the job advertisement to which he or she applied. While this indicator might not be all-encompassing (important aspects like personality or social skills are not covered), it captures the early stages of a job application quite well: a prospective employer is also often limited in his or her assessment of productivity to the signals he or she picks up through the written application of an applicant. To collect data on the matching quality, an extensive data collection was carried out in one unemployment agency in Switzerland. Data on almost 500 unemployed were collected, along with data on their over 6,000 applications to advertised job positions. The unemployed were asked to collect the job advertisements to which they applied. These advertisements were then coded in terms of occupation, education, language, age and gender requirements, and data on the unemployed was matched against these requirements. Additionally, the work certificates of the unemployed were coded and added to the dataset, was general information on their education and former function. In additional estimations, measurements of application behaviour and occupational distribution were introduced, thereby holding these factors constant. Altogether, group differences could be stripped of several potentially important factors influencing the differences in the labour market outcome.

This study does not focus on the difference in wages between job seekers of local and foreign origin, but in the tradition of correspondence testing on another labour market outcome: the probability to be invited to a job interview. In contrast to experimental correspondence testing (as famously used by Bertrand and Mullainathan (2004) for example), the design used in this study is purely observational and no fictional applications are sent out to employers. This has the advantage that applications are as real as possible and that the number of observations can be increased. Because the used data set is very rich, many variables can be held constant despite the non-experimental design.

The results of the estimations are surprising. Comparing the group averages in a simple regression without controlling for the matching quality, application behaviour and occupational distribution, foreigners do slightly better than Swiss job seekers: The interview probability for foreigners is 0.0014 higher than the one for Swiss. This small effect (it's the equivalent of 3.2 % of the average interview probability in the sample, 0.0431) is not statistically significant. The positive coefficient is still highly surprising as one might have expected a negative coefficient, reflecting an advantage of the local job seekers. Further estimations show that this advantage is confined to foreigners from a neighbouring country which experience a very large advantage compared to the Swiss unemployed (+ 0.0436) while other foreigners have a slight to a large disadvantage, depending on their region of origin. In some very broad interpretations of the concept discrimination it is argued that the pure group differences are the best measure of discrimination as pre-labour market determinants of productivity or job choices are themselves nothing but the outcome of discrimination. This argument does not seem applicable to the discrimination of foreigners who might have been educated and trained in another county. To collect evidence on the existence of discrimination how the concept is commonly understood - direct discrimination by employers - productivity would ideally be hold constant. While this is not fully accomplishable – in many industries productivity is even for employers difficult to measure, and getting data on their measurements is usually not feasible – productivity has to be approximated as far as possible.

To do so, a set of matching variables, the level of praise in work certificates and the highest attained education and former function of the unemployed person are included into the estimation. The inclusion of these variables has a strong impact on the coefficient which indicates the interview probability of foreigners compared to the one of Swiss job seekers. The coefficient jumps from a small 0.0014 to a much larger effect of 0.0148 (this coefficient is still not statistically significant however). The change in the size of the coefficient is driven through the inclusion of the matching variable and among these variables it is primarily the local language (German) requirement which plays a large role. It seems that job seekers with only basic local language knowledge get heavily punished. Unemployed with medium and high levels of German knowledge are not disadvantaged against native German speakers however.

In a next step, the application behaviour is held constant (through adding variables on the method of applying, on public and private placements and on the search intensity). This changes the difference in favour of the Swiss (with controls for the application behaviour and duration, the difference is -0.0039). Foreign unemployed seem, in general, to use particularly effective ways to apply more frequently than Swiss unemployed do. Once this influence is held constant, the size of the coefficient decreases. In a third step, variables are entered to control for the occupational distribution. This increases the chances of foreigners, as they generally apply to job openings with more competition (that is to jobs categories characterized through a higher unemployment rate). Once this effect is held constant (through adding industry dummies to the model, occupational dummies or directly through adding the number of unemployed in the occupation) the chances of foreigners are increased.

If the productivity related measures and the control variables for application behaviour and occupational distribution are added together, the foreign coefficient jumps from 0.0014 (without controls) to 0.0257. This is a very large coefficient, statistically significant on the 5

%-level. The main force behind this change is the inclusion of the language dummies. This is a very interesting and to a certain degree puzzling result: Employers seem to favour foreigners over Swiss citizens once the language component is kept constant. A possible explanation – which can not be tested with the data at hand however – is that there is a selection process and that foreign unemployed with good job chances stay in the country while unemployed with lower chances might be more likely to consider returning to their country of origin. This would also explain why the interview probability is particularly high among job seekers from neighbouring countries as these unemployed might be more likely to return than foreigners from further away (of course, this is at least partly also due to the cultural familiarity of employers and such job seekers with each other).

In a final estimation, interactions between the foreign origin and other characteristics are analysed. Additional dummy variables are included into the model which indicate if the person is a women, a person aged 30 years or less, 50 years or more, and if the person is a long term unemployed (the unemployment spell has already lasted for more than a year) or not. This estimation shows that the foreigner coefficient is very stable when those new group dummies are added: It is not just a spurious correlation (at least not one with one of the tested group dummies as the confounding factor). The results also show a large heterogeneity behind the average effect for foreigners. While male foreigners have a strong advantage over male Swiss, female foreigners have an even larger one. There are even larger differences to be found between the different age groups. It seems that the advantage of foreign job seekers is purely determined through the middle age category (31 to 49 year olds). Among the unemployed younger and older than this middle age group, Swiss have a higher interview probability than foreign job seekers. In terms of the long term unemployed, the overall positive result for foreigners is robust: both short term and long term unemployed of foreign origin have an advantage over the short and long term unemployed Swiss respectively.

The paper is structured in the following way: In section 2, an overview over the previous literature and theory is given. The data used is described in section 3. Section 4 assesses the simple group difference uncontrolled for other influences, while section 5 introduces step-wise groups of control variables to hold productivity related measures, application behaviour and occupational distribution constant. Section 6 analyses the interaction between foreign origin and other characteristics (gender, age and duration of unemployment). Section 7 concludes.

2. Theory and related literature

According to the simplest definition, discrimination is an act of treating “equals” unequally (for a discussion of the definition, see Pager and Shepherd 2008). As Amartya Sen (1992) wrote, a central question in the assessment of (in)equality is, “equality of what?”. On the labour market, which has received most attention of economic discrimination studies, the most often used measurements are productivity and salary: Discrimination is systematically remunerating equally productive individuals differently because of the group they belong to. In his pioneering work, Gary Becker (1957) argued that some employers have a “taste” for discrimination and are willing to pay respectively forego part of their profit to maintain distance from members of a particular group. In competitive labour and product markets, rational employers would hire groups of workers which are currently paid less than their productivity is worth. Discriminating employers would thereby suffer a loss of competitiveness which would eventually drive them out of the market. This has not happened (although there are signs that discrimination has diminished over the past decades). Several theories have been put forward to why discrimination persists in the labour market (Darity and Mason 1998 and Figart 2009).

One explanation for this persistence, put forward by supply-side human capital theory, is that the salary differences actually reflect differences in the productivity and are not real discrimination after all. Women for example might invest less in their education in anticipation of spending less time in the labour market through child-birth and possibly a stronger preference towards family life. That decision would also explain why women earn less. The wage difference would not be generated through the labour market and therefore the gap could not be considered discriminatory behaviour by employers (Figart 2009). Other theoretical approaches acknowledge discrimination, and make amendments to the theory why discrimination continues to exist. One approach is simply that markets are imperfectly competitive and that this permits discrimination to persist (Darity and Mason 1998). A second approach, the theory of statistical discrimination, suggests that potential employers cannot observe the true productivity of a job candidate. They use characteristics associated with groups to compensate for the lack of information on the candidate Kennelly (2003). While this might explain why individuals get over- or underpaid, it does not explain why the group average should deviate from its legitimate value. Darity and Mason (1998) criticize the model of statistical discrimination as the authors think that employers should learn if their assessment is erroneous (that is, a group’s productivity is misjudged) and adapt their judgement. However, this adaptation might not happen if it is more expensive to communicate with a minority group (Lang 1986), or assess that group (Cornell and Welch 1996). Dickinson and Oaxaca (2006) show that statistical discrimination can also happen if the estimation is less accurate and therefore more variable. Risk-averse employers would prefer a group which they can judge in a more exact way, generally local workers (even if the estimated group means are the same). Rooth (2009) shows that attitudes and stereotypes are often operated in an automatic, less conscious mode and that discriminatory behaviour against foreigners might be driven through automatically activated associations.

In terms of the interview probability, which will be assessed in this study, an interesting hypothesis stems from Bergman (1974). Her overcrowding hypothesis states that women "crowd" in a subset of occupations, due to societal pressure. This might also be applicable to foreigners if society allows them explicitly (through regulation) or implicitly to work only in certain occupation. The oversupply of labour in these occupations brings the salaries down (see also Usui 2009 and Bergmann 2007). As Kalleberg (2003) noted, this segmentation can also take on new forms like "insiders" having traditional employment relations while "outsiders" having non-standard work arrangements, like temporary work.

When empirically measuring the discrimination, a direct comparison between groups in terms of salary, employment prospects etc. can be interesting because it captures the overall difference to the average, no matter how these differences came about. However, in order to understand the causalities behind a certain pattern, and to assess if direct employer discrimination exists, a direct comparison is not very illuminating, since the differences might be productivity related. An often used approach to estimate the direct discrimination is running a regression, using salary or occupational status as the dependent variable. On the right side of the equation different variables are entered to hold productivity related measures constant (like education, experience and job tenure) and a dummy variable for the group of interest (foreigners for example) is added. If that dummy variable is statistically significant after holding all other productivity related variables constant, the so estimated group difference can be cautiously interpreted as (positive or negative) discrimination (Darity and Mason 1998).

A second often used method is the Blinder-Oaxaca technique, developed by Oaxaca (1973) and Binder (1973). Two separate wage regressions are run, one each for the discriminated group and the non-discriminated group (say foreigners and locals). The difference between the two group averages in the labour market outcome is then divided into two parts. One part is due to the differences in the values of the determinants between the two groups and is called the explained part. The second unexplained part is due to different wage regression coefficients and could be considered as discrimination (Darity and Mason 1998). In a meta-study, Weichselbaumer and Winter-Ebmer (2003) assessed 457 of such (gender wage gap) studies and came to the conclusion that even a very extensive specification of the model cannot explain the whole wage difference – there is always an unobserved part. However, the unexplained part might just simply be due to unobserved characteristics not included in the model and might not be evidence of discrimination (Oreopoulos 2009). The regression approach with group dummy variables and the Blinder-Oaxaca method should generally arrive at a similar conclusion regarding the discrimination. The Blinder-Oaxaca estimation has the advantage that it allows for a more flexible estimation: While the regression approach assumes that the wage equation is the same for both groups, the Blinder Oaxaca does explicitly not (Darity and Mason 1998).

Because of the availability of data, salaries have been the focus of the economic discrimination literature. However, a new branch of literature has focused on the probability to be invited to a job interview, after one has written an application. This so called "correspondence testing" method is usually conducted in the following way: Two fictional applications are sent out which differ only in the gender or nationality of the applicant (without changing any productivity relevant information), and the researcher compares the success of both applications. A good overview over correspondence testing is given by Bertrand and Mullainathan (2004) who used the approach utilizing African-American and white American-sounding names to test for discrimination. They have found that white names have a 50 percent higher probability to be invited to a job interview, and that this gap applies across occupation, industry, and employer size. The same authors (together with two other researchers) have recently used the approach again to measure labour market discrimination of job seekers of different casts in India (Banerjee et al. 2009), where they generally did not find signs of discrimination. The method has further been used by Oberholzer-Gee 2008 with applications from unemployed and employed to test for an unemployment stigma. In other recent papers, Carlsson and Rooth (2007) measured the effect of different ethnic backgrounds and Drydakis (2009) the effect of the sexual orientation of the applicant on the application success.

A strength and a weakness of correspondence testing is the fact that it only observes the application process up to the job interview, and does not take into account what happens after it. It's a weakness because ultimately, one would be interested in the overall differences in the probability to get a job. However, the job interview itself contains so many unobservable processes and characteristics (for example the appearance of the applicant, see Rooth 2009), that it is very difficult to control for them. In so called "audit studies" actors are used to measure the difference in outcome of the job interview. However, with this method it is difficult to provide proof that the matched testers are really identical in every aspect, including their social and communication skills. The experiment is not double-blind and an actor might consciously or unconsciously influence the outcome. Since these studies are expensive, the number of observation is much smaller (Bassanini and Saint-Martin 2008). Bassanini and Saint-Martin 2008 also argue that there is usually no reverse discrimination found in such audit studies (negative discrimination in the written application process and then positive discrimination during the job interview process - or the other way round). Therefore, discrimination in the first stage of the application process does provide at least evidence of the presence and direction of the overall hiring discrimination.

In this study, in contrast to the way correspondence testing is usually used, no fictional applications were created. Instead, information was collected on the real applications sent out by unemployed job seekers. This has the advantage that applications are as real as possible. Forging applications can be difficult for researchers if applications from a whole range of educational and occupational backgrounds have to be mimicked. Through the observational approach, a larger number of applications can be assessed as the method is less time-consuming. Although fewer variables can be held constant than in the experimental design (like the quality of the cover letter for example), the compiled data set is very rich and contains many variables describing the unemployed. It also includes data on the quality of his or her reference letters (in Switzerland, it is standard to attach them directly to the written application).

3. Data

Data on the application process is systematically gathered in all Swiss unemployment insurance agencies, using a self-reporting sheet filled out by the unemployed person. The unemployed track all their applications over the course of a month and hand the sheet over to the case worker at the end of the month. Most of these forms are filled out by hand, and while they are archived for quality checks and lawsuits, the information isn't stored electronically. The data has not been used for research so far. In order to make this data source accessible, the data on the application sheets have to be stored electronically. This has been done in one agency of the Swiss Unemployment Insurance, the Zurich-Staffelstrasse agency. Being a medium sized agency with both clients from city and rural areas and with a wide variety of occupations, this agency seemed well suited. Obviously, the data cannot be considered representative for the canton of Zurich or Switzerland as a whole, but it gives important insights. The data was gathered between 1st of July 2007 and 31st of March 2008.

Of all the unemployed registered during this time, a stratified sample was taken: This sample contains all unemployed with at least one participation in an Active Labour Market Program (a quarter of all unemployed registered at Zurich-Staffelstrasse) and a random selection of a third of the spells in which the unemployed did not attend such a program. The reason that the sample was taken with this stratification is that the data was also used to evaluate Active Labour Market Programs (see the first essay of the thesis). From this sample, all applications within the lay-off period (the person wasn't unemployed at any point of the spell) and applications during the last month of unemployment were dropped, as these periods are subject to different rules by the unemployment insurance. Including them would distort the analysis. The sample was then further restricted to applications to advertised job openings as the estimations use data from the job advertisements (to identify to quality of the match between the job opening and the applicant).

The unemployed were asked to collect the advertisements of job openings they applied to (if the open positions were advertised). Altogether, 6637 job advertised of 467 were collected and then coded by the research team. This very time-intensive process was crucial to this study, because the data on requirements could then be compared to the skills and characteristics of the unemployed person. Thereby, an individual matching between the unemployed and the job opening could be calculated. While 6637 job advertisements is a very large number, please note that this is only 43.7 % of all job advertisements which could have been brought in if the advertisements would have been collected for every single application to an advertised job opening (altogether 15,198). 117 unemployed didn't bring in a single cut-out job advertisement. Among the ones who did, the average unemployed brought in every second advertisement (49.6 %) to the next counselling session. This raises questions how representative the sub-sample is.

Table 1 shows that the sub-sample "applications with a recorded job advertisement" is surprisingly balanced when compared to the total sample of "applications to advertised job openings". Applications from women, younger and older unemployed and long term unemployed are very similarly distributed in both groups. However, the unemployed who collected the advertisements were more often Swiss unemployed than in the overall sample of applications to advertised job openings. The reason for this is most likely language barriers: Some unemployed did not understand what was asked of them. However, even between Swiss and foreigners, the balance is kept quite well. The table also shows the balance for an indicator which captures the overall chances of an unemployed to find a job, as assessed by the case worker. This indicator is a forecast by the case worker at the beginning of the unemployment spell, and the table shows the proportion of unemployed with a forecast of 12 months and more (a long term unemployment forecast). The average unemployed in the sub-sample of those who handed the job advertisement in is slightly less likely to become long term unemployed in the eyes of the case workers, but the difference is small. A final comparison assesses the search intensity, measured as the average number of applications written in the week the application was sent off. As one would expect, this number is slightly higher in the sub-sample of unemployed who brought the job advertisements with them (because both, high search intensity and following the request to bring the advertisements along, might be a sign for motivation during the job search). Again, the difference is small and the sub-sample is largely representative also in this aspect.

	Applications to advertised job openings	Applications with a recorded job advertisement
Foreign origin	0.5207	0.5841
Women	0.4809	0.4759
Age <= 30	0.1871	0.1938
Age >= 50	0.2346	0.2210
Long term unemployed	0.2557	0.2547
Unemployed has a long term unemployment forecast	0.5048	0.4655
Search intensity (number of applications in the week the application was sent off)	3.7201	3.7915
N (applications)	15,198	6637
N (unemployed)	584	467

Table 1: Balance of sub-sample with recorded job advertisement compared with overall sample

Note: Weights are used to compensate for stratified sample.

Altogether, the data collection led to a database containing data of 6637 applications of 467 unemployed persons. The number of observations decreases steeply as the duration of the spell increases; more and more unemployed leave as they find a job. The case number can be low when looking at the later stages of the unemployment spell (see Figure 1). Because of the stratification, data will be weighted in order to represent the proportions in the overall population.

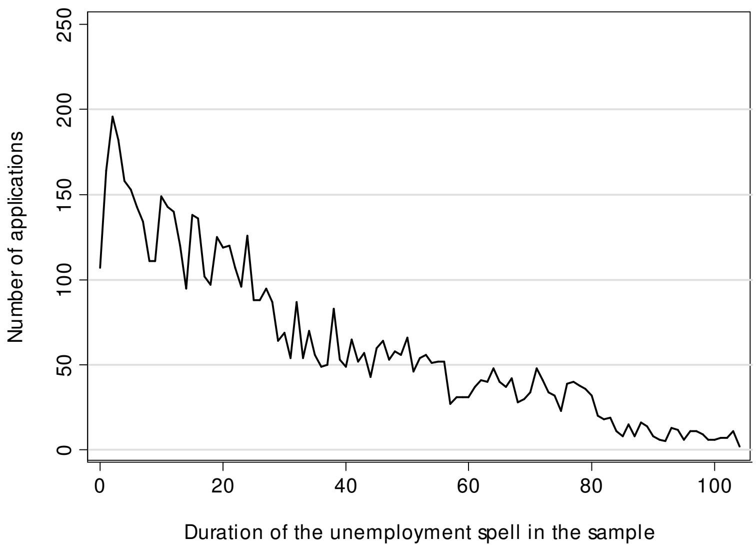


Figure 1: Development of the number of applications in the sample
Note: The graph shows the number of observation covered in each week. The duration is plotted until the 104th week, after which the entitlement time frame expires. A total number of 467 unemployment spells are observed. Because of left and right censoring this total number is not reached in any of the weeks.

Figure 2 shows the development of the proportion of applications which stem from foreigners. The ratio changes over time: There are more applications from foreigners as time passes by. The changing proportion is interesting for one part because this is an indicator of application success: an unemployed with a higher interview probability will also leave unemployment quicker than others. The shifting proportions might also pose a problem for the estimation however, because if there are fewer applications from Swiss citizens at a later stage of the spell, this might lead to a higher overall average interview probability of that group (as applications later in the spell have a generally lower chance than applications early in the spell). To further assess if the results are robust towards these changes in the sample, two separate estimations will be conducted for applications from an early and a late period in the spell.

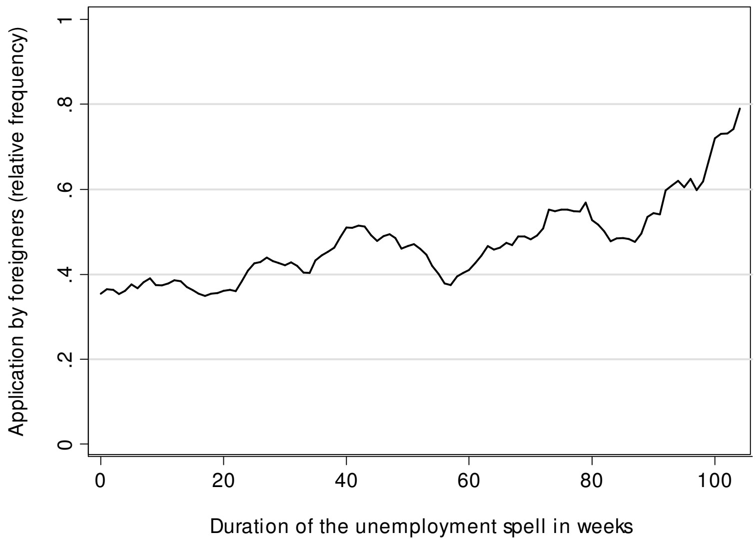


Figure 2: Development of the relative frequency of applications by foreigners
Note: The graph shows the proportion of applications in the sample which were written by foreigners, per week. The duration is plotted until the 104th week, after which the entitlement time frame expires. A total number of 467 unemployment spells are observed. Because of low observational numbers in certain weeks, a nine week moving average is used.

Two general objections to the data quality could be raised, both in connection to the self-reporting nature of the application sheets. The first possible objection could be that not all records are truthful and that some unemployed record applications they have never written. While wrongly recorded data (on purpose or by mistake) cannot be ruled out, the amount of purposeful cheating should be rather small, as case workers regularly check back with employers if the unemployed have indeed applied to the job indicated on their self-reporting sheet. The second objection could be that because of the requirement to write at least 8 to 12 applications, many unemployed don't bother writing all their applications down and instead stop once the minimum has been reached, therefore depriving the dataset of all their other applications. Again, this doesn't seem to be the case, neither according to statements by the case workers, nor showing up in the data. The applications are more or less evenly distributed over the stretch of a month, both the ones from Swiss and foreign unemployed (see Annex 1). If only the first 10 or so applications would be recorded, one would expect an accumulation at the beginning of the month.

There is one more issue which has to be addressed in connection to the reporting sheet: Among other entries, the unemployed record the outcome of the application, whether they had an interview, a job offer or a rejection. The case workers at the trial agency reported that there was some confusion about the meaning of “job interview” when unemployed were carrying out personal applications (showing up at a company's door step and asking for a job). A few unemployed recorded such a personal application as an interview. The avoid any bias, the data from unemployed who declared all their personal applications as a success were left away (this is already incorporated in the above mentioned observational numbers).

Apart from the self-reporting application sheets, data sources used include the database of the Swiss unemployment insurance on registered unemployed persons, and a survey conducted among case workers (to gather data on the unemployment duration forecast and the quality of the work references).

4. Differences in the probability to be invited to a job interview

Traditionally readily available data like the unemployment duration shows large differences between Swiss unemployed and unemployed with another nationality: While the average unemployment spell lasted 181 days (median value of the unemployed covered in the dataset), it was 169 days for Swiss and 203 days for foreigners. Among those who left the unemployment insurance during the observational period, 75.6 % reported that they deregister because they have found a job. Among Swiss (78.7 %) this proportion is higher while for foreigners (71.0 %) it is lower. This simple comparison shows that there are indeed large differences between the two groups, to the disadvantage of foreigners. The question this study seeks to answer is, what differences between the two groups can be found in the probability to be invited to a job interview once an unemployed person has sent his or her application off? This probability will be first estimated in a very simple regression where only a minimum of influences are held constant (the duration of the spell at the time) and later in successively more complex models through which many influencing factors are held constant (productivity related measures, application behaviour and occupational distribution).

The following regressions are all conducted in a similar fashion. As the dependent variable, the model contains a dummy variable indicating if the application was a success. The dummy takes the value 1 if the application results in a job interview and 0 if it doesn't. The mean value for this variable is 0.0431 which means roughly every 20^{th} application is successful (see Annex 2 for the summary statistics per group). On the right side, a dummy variable which switches to one if the applicant is of foreign origin is entered into the estimation. The coefficient of this dummy measures the difference in the application success between Swiss and foreigners. Additional estimations are conducted where the simple dummy variable for foreigners is further split into dummies for foreigners from different regions (most of these estimations can be found in the Annex). Additionally, duration dummies are entered which indicate in which month the application was sent off. This is important because the interview probability falls quickly over time (see the first essay of the thesis). By including these dummies, one can also counteract the misbalance in the sample which stems from the fact that the majority of applications late in the unemployment spell are sent of by foreigners while the majority of early applications are written by Swiss citizens (see Figure 2).

Then (in the next section) further variables are entered to control for influences which might distort the identification of a potential discrimination. The estimations are conducted by the OLS method, and heteroskedasticity robust standard errors are reported (the errors take into account that some of the applications are clustered, i.e. from the same person).

In a first step, simple OLS regressions are run to estimate the difference between Swiss and foreign job seekers in their job interview probability (Table 1). The results show that on average, foreign unemployed have practically the same chance to be invited to a job interview. The probability is actually slightly higher for foreigners (+ 0.0014) but the difference is very small (it's the equivalent of 3.2 % of the average interview probability in the sample, 0.0431). This small difference is not statistically significant. There does not seem no be any overall difference which manifests itself directly on the nationality (at least none which shows up on the interview probability). This finding is very surprising; from literature, similar correspondence studies and descriptive statistics on other labour market outcomes (like wages) one would have expected foreigners to have a much lower interview probability for foreigners. It's also surprising if one compares this result with the above mentioned average duration of an unemployment spell which shows that on average, foreign unemployed are unemployed for a longer period of time. Possibly Swiss unemployed fare better in the job interview situation and counteract this initial advantage of foreigners. Another explanation could be that foreigners apply on average to jobs where more applicants are screened in the interview process. This would allow them to enjoy a high probability to be invited to a job interview but it would not increase their overall chance to receive a job offer.

Dependent variable: Interview Probability		
Mean	0.0431	0.0431
Std. Dev.	0.2031	0.2031
Foreigner	0.0014	
	(0.0082)	
From a neighbouring country		0.0436**
(Austria, France, Germany, Italy, Liechtenstein)		(0.0166)
From an EU or EFTA country		-0.0072
(other than the neighbouring countries)		(0.0177)
From an non-EU / non-EFTA country		-0.0114
		(0.0085)
Duration (13 dummies, omitted: Month 1)	yes	yes
Constant	0.0768**	0.0728**
	(0.0124)	(0.0124)
Sample		
Number of measurements	6637	6637
Number of unemployed	467	467
Estimation		
R-squared	0.0092	0.0141
F-value	2.5938	3.0891

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The 13 duration dummies are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.

Table 2: Interview probability of unemployed of different origins

It is possible that very heterogenous interview probabilities hide behind this aggregated dummy for foreigners, depending on the region the foreigner comes from. Because of the limited number of unemployed covered in the study, it is not possible to estimate the effects for the unemployed of single nations. Therefore, broad regional dummies are entered: foreigners from a neighbouring country, foreigners from another EU-27/EFTA country (from one of the 27 member states of the European Union or from one of the four member states of the European Free Trade Association), and foreigners from outside the EU-27/EFTA area. The first of these three groups could have an advantage because of the cultural familiarity (of both the job seeker and the employer with each other) and because the neighbouring countries share the national languages of Switzerland. Both other groups might not share the above mentioned advantages but they still have access to the Swiss labour market (otherwise they would not be able to obtain unemployment compensation).

The second column in Table 2 shows the results of the estimation with the differentiated foreigner variable. The results indicate that there is a very large positive effect for foreigners migrating from one of Switzerland's neighbouring countries (Austria, France, Germany, Italy and Liechtenstein). That group of unemployed has an interview probability which is 0.0436 higher than the one for Swiss unemployed. This very large difference (it's as high as the average interview probability in the sample, 0.0431) is statistically significant on a 1 %-level.

The coefficient for the group of foreigners from an EU-27/EFTA countries is slightly negative (-0.0072) and the coefficient for foreigners from a non-EU-27/EFTA country (this is geographically a very diverse group obviously) is strongly negative at -0.0114. Both coefficients are not statistically significant. It seems that the positive foreigner effect is limited to the neighbouring countries. While these differences between Swiss and foreigners as captured in Table 2 and 3 are interesting themselves, they are not proof that discrimination does or does not exist, as productivity related measures for example are not held constant.

5. Holding productivity related measures, application behaviour and the occupational distribution constant

In order to reject the interpretation of simple group comparisons of labour market outcomes as a sign for discrimination, two arguments are usually used. One is that groups vary in productivity and that this has to be taken into account. Foreigners might experience worse (or better) labour market outcomes because they have higher (or lower) education or lack of local language knowledge. The other one is that it might be a matter of choice where people like to work and that some jobs might be remunerated less because they are more enjoyable in other ways (Figart 2009). Foreigners could have a better labour market outcome because they work in more dangerous jobs for example. In order to show that differences in labour market outcomes might indeed be due to some form of discrimination, one has to show that these differences still exist, even with productivity related measures and the occupational distribution being held constant. As a third possible explanation for differences in the interview probability, the application behaviour of the unemployed will also be examined.

The first group of variables tries to approximate the unobservable productivity of an unemployed person. Note that the productivity is also not directly observable to the employer, especially not that early in the application process. Ideally therefore, in trying to find a discriminatory component, one should choose the same or similar measurements of productivity the employer would use when receiving an application. The most important indicators of productivity for an employer are probably the quality of the match between the job requirements and the skills, education and experience of the job seeker. This match is usually hard to include in studies because of the lack of data on it. However, for this study over 6,000 job advertisements were collected, coded and recorded which made it possibly to match the requirements against the data available on the unemployed in the database of the unemployment insurance. Through this, several variables showing the matching quality could be calculated: The occupational match (previous occupation of the unemployed versus occupation mentioned in the job advertisement), educational level, knowledge of the German language, age and gender. In case of occupation, German knowledge and gender the matching variable is a dummy variable switching to 1 if the requirement is fulfilled. In case of education and age, where the unemployed can have a value too low or too high, a set of dummies is used (education is split into “requirement fulfilled, “overqualified” and “underqualified”, and age is split into “requirement fulfilled”, “too old” and “too young”). For each set, there is also a dummy variable indicating if there was no requirement mentioned in the job advertisement.

Next, the level of praise in the last three work certificates is introduced. In Switzerland, it is common to attach a copy of the last few work certificates to the application and they seem to be treated with importance (as public debates over them regularly show). As good or very good work certificates are common (see the summary statistics in Annex 2), one would expect that mainly sub-standard work certificates leave their mark on the chances of a job-seeker. Therefore, not the average level over the last certificates is added the model, but instead the lowest level of praise found in any of the last three certificates. Three dummies are included, one dummy for a unsatisfactory minimum level of the certificates, a dummy for a satisfactory level and one dummy for a good to very good level.

A third estimation assesses if the results change if the highest education (5 groups are distinguished) and the former function level (three groups are distinguished: management, professional and low-skilled level) of the unemployed are added as further explanatory variables. The educational match has already been included as part of the matching variables, but it’s possible that education has an influence beyond the pure match with the requirements: It might (or might not) signal to employers a quick grasp of things, willingness to learn and persistence. Experience in the occupation could also be included among these general productivity related variables, but the database of the unemployment insurance lacks data on it.

The results in Table 4 show that compared with the original result (Table 2) indeed a large change to the group coefficient is noticeable once the matching quality is held constant. When the matching variables are added, the coefficient for foreigners experiences a huge increase, from a coefficient close to zero (0.0014) to a strong positive one (0.0211) which is significant on a 5 %-level. The relative size cannot easily be compared to the constant as the constant now represents a Swiss unemployed who does not fulfil one single requirement mentioned in the job advertisement. The coefficient is best compared to the overall average interview probability for all unemployed (at any stage of the spell), 0.0431. The difference is 49.0 % of that average.

The fact that the foreigner coefficient rises once the matching variables are introduced shows that the match with the requirements is often quite bad for foreigners. The summary statistics in Annex 2 point to the local language knowledge requirement which is most often not fulfilled. Indeed, only 10.2 % of all applications written by foreigners fulfil the German requirement, while 58.5 % of the applications don't fulfil the requirement and 31.3 % of the applications are directed to advertisements which did not mention a German requirement. For Swiss, the respective proportions are 34.6 % (fulfilled), 12.4 % (not fulfilled) and 53.1 % (no requirement). The relatively high number of applications by Swiss unemployed who do not fulfil the German requirement probably stem from Swiss unemployed who are originally from another region of Switzerland (where one of the other three national languages is spoken; French, Italian or Rhaeto-Romanic), or from persons who migrated from another country and have acquired Swiss citizenship in the mean time. As the language requirements mentioned in the job advertisement and the skills recorded in the database do not have the same coding, a conversion rule had to be applied. Possibly, the language matching criteria was chosen too hard – after all, a large proportion of the unemployed fails to fulfil it, both of foreign and Swiss origin. However, test haven shown that loosening the criteria does not change any of the results. Employers seem to favour foreigners over Swiss citizens if the language component is kept constant – this result is both surprising and puzzling in as far what could be the root cause for this.

Next the minimum level of praise in the last three work certificates is introduced. If this level of praise is held constant, the foreigner coefficient is slightly increased compared to its original size. The new dummy variables seem to compensate for the fact that foreigners have more often insufficient work certificates (an insufficient work certificate is attached to 15.8 % of the applications by foreign unemployed compared to 9.0 % applications from the Swiss unemployed). Also, 22.8 % of applications from foreigners do not have a work certificate attached at all (compared to 10.9 % of the Swiss applications). This might also have a negative impact. The reason for the lack might be that the foreigner comes from a country where written work certificates are not common practice. A Swiss employer however might interpret the fact that an applicant does not attach such work certificates as a signal that the job seeker has not worked at all before, that she or he had temporary jobs for which no job reference was received, that he or she had a bad relationship to the previous employers or that the certificate was so bad that the job seeker prefers not too reveal it.

The fourth and last column enters the highest education and the former function level of the unemployed as independent variables. Adding these variables does also increase the coefficient of foreigners. Foreigners (at least the unemployed ones) possess more often than Swiss job seekers either a weak or strong formal education, while Swiss job seekers are more equally distributed over the different educational categories: 62.4 % of foreign unemployed have no further education beyond compulsory schooling. Among Swiss, this proportion is 16.5 %. However, 10.6 % of foreign job seekers have a university degree, while among Swiss this is slightly less at 10.4 %. The regression results show (coefficients are not displayed in the tables) that education has a strong influence on the interview probability; the higher the education, the better the chances. In the case of foreigners, the high number of job seekers without further schooling or vocational training reduces the overall interview probability of the group. Once this influence is held constant, the foreigner coefficient rises to a higher level.

The coefficient for foreigners is much higher than the original coefficient from the estimation without those variables when all the productivity related measures are added together. While adding any of the controls variables had a positive influence on the foreigner coefficient, it was clearly the matching variables which raised it to its highest level. Adding all control variables together, the coefficient for foreigners is actually slightly lower than in the estimation with just the matching variables. It seems that the impacts of the control variables cancel each other out to a certain degree. However, the coefficient in this final estimation is still of a very large size (but remains not statistically significant).

Differentiating the one dummy variable for foreigners further into dummy variables for the different regions (foreigners from neighbouring countries, foreigners from EU-27/EFTA countries or foreigners from a non-EU-27/EFTA country) continues to result in a very large positive coefficient for foreigners from a neighbouring country and smaller but also positive coefficients for foreigners from the other two regions. These results are shown in Annex 3 (all other tables in the main text are replicated using the three region dummies, and displayed in Annex 3 to 7).

Dependent variable: Interview Probability					
Mean	0.0431	0.0431	0.0431	0.0431	0.0431
Std. Dev.	0.2031	0.2031	0.2031	0.2031	0.2031
Foreigner	0.0014	0.0211*	0.0037	0.0057	0.0148
	(0.0082)	(0.0091)	(0.0086)	(0.0088)	(0.0091)
Match between unemployed person and open position (occupation, education, German, age and gender match)	no	yes	no	no	yes
Level of praise in work certificates (the lowest level in one of the last 3 certificates determines the value)	no	no	yes	no	yes
Highest attained education and former function of unemployed person	no	no	no	yes	yes
Duration (13 dummies, omitted: Month 1)	yes	yes	yes	yes	yes
Constant	0.0768**	-0.0015	0.0548**	0.0520**	-0.0286
	(0.0124)	(0.0230)	(0.0141)	(0.0181)	(0.0260)
Sample					
Number of measurements	6637	6637	6637	6637	6637
Number of unemployed	467	467	467	467	467
Estimation					
R-squared	0.0092	0.0206	0.0113	0.0185	0.0280
F-value	2.5938	2.8700	2.3118	2.6490	2.6595

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The match between the unemployed person and open position is measured in five dimensions (occupation, education, knowledge of the German language, age and gender). Each dimension is measured through a set of dummies (usually requirement fulfilled; requirement not fulfilled; no requirement mentioned in the job advertisement). The level of praise in the work certificate is measured as a set of dummies representing the lowest level of praise in the last three work certificates. The highest attained education is measured through five dummies and the former function of the unemployed through three dummies (low skilled, professional, management). The 13 duration dummies are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.

Table 4: Group specific interview probabilities – controlled for productivity related measures

It remains surprising that foreigners do not have a disadvantage – wether one does or does not include productivity related indicators. Once these variables are introduced, foreigners have a distinct advantage over Swiss unemployed. These positive gains through the control variables are mainly due to introducing a variable which holds the match to the German language requirement of the job, on which many foreigners fare badly, constant. Below, some more estimations will be performed to analyse this finding further.

In Table 5, the first column assesses the impact of the matching variables if all the matching variables but the variables describing the match to the German language requirement are added. The second column shows the estimation if all the variables are included (including the German language match). The results show that the foreigner coefficient is much weaker if the German language match is missing, although the other matching variables also have a strong positive effect on the size of the coefficient. In a next estimation (third column) additional dummies are entered to control for the German language abilities of an unemployed person (the direct match to the German requirement is again removed). The results show that once these dummies are included, the foreigner coefficient becomes highly positive (+ 0.0227) and the difference to Swiss unemployed becomes statistically significant on a 5 %-level. The results also show that the interview probability is very low for foreign unemployed who only speak basic German (this is the lowest level assigned in the assessment): This group has an interview probability which is 0.0565 lower than the one for native German speakers. Equally bad off are persons which have not been tested yet (this might be because there is a high proportion of persons with very low levels of German in this group). Foreigners with a medium or high knowledge of the German language however have no disadvantage over persons with native German knowledge. In fact, medium German knowledge results in an advantage over both native speakers and unemployed with high German knowledge – this is hard to explain, but it might just be due to a random occurrence (the coefficient is not statistically significant).

Adding both language and language matching dummies, the foreigner coefficient is practically the same as the one in the estimation with just the language dummies. In this combined estimation the coefficients of the language matching dummies are only a bit smaller while the German matching dummies fare quite a lot weaker. However, fulfilling the language requirement still has a strong positive impact, despite holding language knowledge constant – it seems that both matching the requirement and general language knowledge matter.

Dependent variable: Interview Probability				
Mean	0.0431	0.0431	0.0431	0.0431
Std. Dev.	0.2031	0.2031	0.2031	0.2031
Foreigner	0.0079	0.0148	0.0227*	0.0228*
	(0.0092)	(0.0091)	(0.0100)	(0.0100)
Match with German language requirement mentioned in job advertisement				
Requirement fulfilled		0.0379**		0.0094
		(0.0106)		(0.0125)
No requirement mentioned		0.0174*		-0.0017
		(0.0084)		(0.0092)
Knowledge of the German language (omitted category: native German)				
Basic			-0.0565**	-0.0522**
			(0.0139)	(0.0143)
Medium			0.0260	0.0298
			(0.0569)	(0.0585)
High			0.0071	0.0064
			(0.0204)	(0.0208)
Not tested			-0.0509**	-0.0467**
			(0.0123)	(0.0130)
Match between unemployed person and open position (occupation, education, age and gender match - without German language match)	yes	yes	yes	yes
Level of praise in work certificates (the lowest level in one of the last 3 certificates determines the value)	yes	yes	yes	yes
Highest attained education and former function of unemployed person	yes	yes	yes	yes
Duration (13 dummies, omitted: Month 1)	yes	yes	yes	yes
Constant	-0.0116	-0.0286	0.0309	0.0226
	(0.0254)	(0.0260)	(0.0254)	(0.0261)
Sample				
Number of measurements	6637	6637	6637	6637
Number of unemployed	467	467	467	467
Estimation				
R-squared	0.0250	0.0280	0.0337	0.0341
F-value	2.5413	2.6595	3.2999	3.1165

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The match between the unemployed person and open position is measured in five dimensions (occupation, education, knowledge of the German language, age and gender). Each dimension is measured through a set of dummies (usually requirement fulfilled; requirement not fulfilled; no requirement mentioned in the job advertisement). The level of praise in the work certificate is measured as a set of dummies representing the lowest level of praise in the last three work certificates. The highest attained education is measured through five dummies and the former function of the unemployed through three dummies (low skilled, professional, management). The 13 duration dummies are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.

Table 5: The influence of German language knowledge

Next several variables are introduced to examine if the differences in group specific interview probabilities might be explained through different application behaviour of Swiss and foreign unemployed (Table 6). Two dummy variables are introduced first which indicate if the application was a phone or personal application (the omitted category are the written applications). Both phone and personal applications have a considerably higher interview probability than written ones, and it’s therefore possible that a group using one of these methods more frequently achieves a higher overall probability. Indeed, the foreigner coefficient turns from slightly positive (with no control variables apart from the duration dummies, first column) to slightly negative (additionally controlled for application method, second column). Foreigners seem to use these productive methods more often then Swiss (see Annex 2) – holding their influence constant, the foreigner coefficient is decreasing. However, the foreigner coefficient remains close to zero and is statistically not significant.

In the third column, two dummy variables are introduced which indicate if the application has been linked to a public placement (by the case worker of the unemployment insurance) or a private placement (by one of the private recruitment agencies). Including data on placements does not change the foreign group coefficient at all. This is perhaps not surprising as placements are quite uncommon (only 7.4 of all applications are linked to a placement). Similarly, adding the search intensity of the unemployed person, measured as the number of applications written in the week the application was sent off, to the model does not change the interview probability of foreigners relative to one of Swiss unemployed by much. While a higher search intensity can decrease the average interview probability (if the unemployed first applies to the position with the highest interview probability, then to the position with the second-highest etc.), it probably also correlates with motivation and the effort put into the applications (and therefore could correlate positively with the interview probability of an unemployed). In either case, this does not seem to affect the foreigner coefficient.

Adding all the variables describing the application behaviour together in the last estimation of this set, the foreigner coefficient reaches its lowest level yet. However, it is still close to zero and not statistically significant. One can summarize that different application behaviour does not seem to explain much of the difference between the application performance of foreigners and Swiss job seekers.

Dependent variable: Interview Probability					
Mean	0.0431	0.0431	0.0431	0.0431	0.0431
Std. Dev.	0.2031	0.2031	0.2031	0.2031	0.2031
Foreigner	0.0014	-0.0034	0.0010	0.0012	-0.0039
	(0.0082)	(0.0084)	(0.0082)	(0.0081)	(0.0083)
Method of applying (written, phone or personal application)	no	yes	no	no	yes
Placement (public or private)	no	no	yes	no	yes
Search intensity (number of applications written)	no	no	no	yes	yes
Duration (13 dummies, omitted: Month 1)	yes	yes	yes	yes	yes
Constant	0.0768**	0.0701**	0.0769**	0.0756**	0.0687**
	(0.0124)	(0.0125)	(0.0124)	(0.0123)	(0.0123)
Sample					
Number of measurements	6637	6637	6637	6637	6637
Number of unemployed	467	467	467	467	467
Estimation					
R-squared	0.0092	0.0242	0.0093	0.0093	0.0244
F-value	2.5938	3.5781	2.7961	2.5221	3.6568

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
For control for the method of applying and placements two dummies each are entered. The 13 duration dummies are:
1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.

Table 6: Group specific interview probabilities – controlled for application behaviour

A final group of control variables relate to the occupational distribution. It could be argued that by comparing the job interview probability across all occupations and industries, one is comparing oranges with apples if the assessed groups apply in different industries or different occupations (Darity and Mason 1998). These industries / occupations might be feature different levels of competition. The estimations in Table 7 check the validity of that argument and assess if any of the group differences might be explained through the occupational distribution. The battery of tests consists of first adding dummies for each of twelve industries, then refining this broad classification further by adding 119 dummies for the occupations. Note that the estimation is thereby restricted to the intra-industry and intra-occupation variation respectively. In the case of the occupational dummies, one thereby also effectively discards all the information from unemployed who are the only sample member in their occupation (54 unemployed).

There are also arguments against holding the occupational distribution constant in an estimation of group differences. As Darity and Mason (1998) state, the occupational distribution might be a type of discrimination itself (rather than an exogenous factor) if society pushes a group into particular jobs. Bergman 1974 and 2007 has argued in her crowding hypothesis that the occupations which are over-frequented by discriminated groups tend to be over-crowded. The high supply of workers pushes the wages down. Workers of discriminated groups nevertheless don't leave the occupation because societal pressure or government regulations only allow them to work in certain occupations or industries.

One would indeed expect the level of competition around an open position to have a direct and major influence on the interview probability. Unfortunately, the number of applicants is not known. It can be approximated however through the number of unemployed in the occupation to which the advertised position belongs, in the region (the canton of Zurich). On a purely descriptive level, there is some evidence of a possible "over-crowding" in occupations where foreigners apply. The summary statistics show that the average application is sent to a position which belongs to an occupational group with 742 unemployed in the region. Because the region is rather small and accessible, one might be compete with up to 742 other applicants for that job opening (not to forget all the applicants which still have a job, or applications which are willing to commute or to relocate from another region. While for Swiss unemployed this number is 670, foreigners compete with up to 840 potential competitors. In a third estimation, the number of unemployed in the occupation is added to the model (note that it is not the occupation of the unemployed but the occupation of the job opening which is included – of course they might often be the same one).

The results in Table 7 show that after adding the industry dummies, foreigners fare much better. The coefficient grows from 0.0014 to 0.0064. Adding occupational dummies results in changes in the same direction, but the foreigner coefficient grows even more, to 0.0085. Adding the number of unemployed has also the effect in increasing the coefficients, however, the change is quite a weak one, from 0.0014 to 0.0019. The foreigner coefficient remains statistically not significant in all estimation, even when the new control variables are added.

Dependent variable: Interview Probability				
Mean	0.0431	0.0431	0.0431	0.0431
Std. Dev.	0.2031	0.2031	0.2031	0.2031
Foreigner	0.0014	0.0064	0.0085	0.0019
	(0.0082)	(0.0091)	(0.0108)	(0.0083)
Industry (12 dummies)	no	yes	no	no
Occupation (119 dummies)	no	no	yes	no
Number of unemployed in the occupation	no	no	no	yes
Duration (13 dummies, omitted: Month 1)	yes	yes	yes	yes
Constant	0.0768**	0.0739**	0.0706**	0.0789**
	(0.0124)	(0.0167)	(0.0117)	(0.0131)
Sample				
Number of measurements	6637	6637	6637	6637
Number of unemployed	467	467	467	467
Estimation				
R-squared	0.0092	0.0125	0.0619	0.0094
F-value	2.5938	1.7212	1.8177	2.3389

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The number of unemployed in the occupation (119 categories are differentiated) is measured as the total number in the region (the canton of Zurich). The 13 duration dummies are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.

Table 7: Group specific interview probabilities – controlled for occupational distribution

In fact, these changes behave just as expected. Foreigners apply in industries with high competition and therefore below average interview probability. This decreases their chances. Once this effect is held constant (through the industry dummies, occupational dummies or directly through the number of unemployed in the occupation) the chances are increased for foreigners.

After separately holding productivity related measures, application behaviour and occupational distribution constant with their respective sets of variables, it is now interesting to see what happens if they're all included simultaneously in the estimation. Table 8 shows two estimations. The first one contains simply the group dummy for foreigners and the set of duration dummies. The second one contains the group dummy and all discussed control variables, apart from the occupation dummies. Latter are excluded because they might result in an over-specification of the model with their high number of estimated dummies – the effect of an "over-crowding" can also be captured through the industry dummies and the number of unemployed in the occupation.

Dependent variable: Interview Probability		
Mean	0.0431	0.0431
Std. Dev.	0.2031	0.2031
Foreigner	0.0014	0.0257*
	(0.0082)	(0.0111)
Productivity related measures		
Match between unemployed person and open position	no	yes
Level of praise in work certificates	no	yes
Highest attained education and former function of unemployed person	no	yes
Knowledge of the German language	no	yes
Measurements of application behaviour		
Method of applying	no	yes
Placement	no	yes
Search intensity	no	yes
Measurements of occupational distribution		
Industry	no	yes
Number of unemployed in the occupation	no	yes
Duration (13 dummies, omitted: Month 1)	yes	yes
Constant	0.0768**	0.0136
	(0.0124)	(0.0281)
Sample		
Number of measurements	6637	6637
Number of unemployed	467	467
Estimation		
R-squared	0.0092	0.0533
F-value	2.5938	3.4068

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The match between the unemployed person and open position is measured in five dimensions (occupation, education, knowledge of the German language, age and gender). Each dimension is measured through a set of dummies (usually requirement fulfilled; requirement not fulfilled; no requirement mentioned in the job advertisement). The level of praise in the work certificate is measured as a set of dummies representing the lowest level of praise in the last three work certificates. The highest attained education is measured through five dummies and the former function of the unemployed through three dummies (low skilled, professional, management). For both method of applying and placements two dummies are entered. The number of unemployed in the occupation (119 categories are differentiated) is measured as the total number in the region (the canton of Zurich). The 13 duration dummies are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.

Table 8: Group specific interview probabilities – controlled simultaneously for productivity related measures, application behaviour and occupational distribution

The results show that overall, the foreigner coefficient is greatly increased, from 0.0014 to 0.0257, when all controls are added. The latter coefficient is statistically significant on a 5 %-level. These results confirm what has already been found in the previous estimations: Once productivity related measures, application behaviour and occupational distribution are held constant, foreigners have a distinctive advantage over Swiss. The previous estimations have also shown that holding the application behaviour constant does not change a great deal. However, holding productivity related measures (among it, most importantly, language knowledge and the match with the language requirement) and the occupational distribution (and thereby the distribution into jobs with a high or low competition) constant, increases the chances of foreigners, as they have both a generally bad match with the language requirement and are distributed into jobs with a high competition.

As discussed in the data section, the proportions of applications stemming from foreigners changes over time. This fact can have an influence on the estimation. For example, if there are more applications from foreigners later in the unemployment spell (Figure 2), this might lead to a lower overall average interview probability, as applications early in the spell have generally a higher chance than applications later in the spell. In order to test for this affect, Annex 8 replicates the estimations shown in Table 8, but this time the estimation is conducted separately for the two following duration groups: Applications in month 1 to 6 and applications in month 7 and later. This split was chosen because it divides the sample roughly in half. The estimation results show that the foreigner coefficient has the same sign no matter if one uses all applications, only applications during the first six month or only applications from month 7 onwards. However, the coefficient is much larger in the first period (+ 0.0330). In the second period the coefficient is decreased (0.0107) and not statistically significant. Nevertheless, 0.0107 is also a large difference between the two groups.

6. Interaction with gender, age and unemployment duration

So far, foreigners have been studied as one large homogenous group. However, in calculating the average effect, one might miss important differences within the group itself. In order to unveil more of this in-group heterogeneity, the interaction of the dummy variable for foreigners with other group dummy variables is assessed. Especially other groups which might potentially experience discrimination themselves are of interest. Four groups of unemployed are analysed in this way: women, younger unemployed (30 years of age and younger), older unemployed (aged 50 and older) and the long term unemployed (unemployed with a spell duration of more than a year). Gender specific differences in labour market outcomes have been – together with differences between foreigners and locals - a main focus of the discrimination literature. It seems interesting to broaden the spectrum of potentially discriminated groups and also include age groups, on which a lot of political discourse has been initiated in many countries. In Switzerland, the debate has been sparked through very high youth unemployment (very high for the generally low Swiss unemployment rates at least) during the last peak of unemployment. Older job seekers also experience a high unemployment rate which is characterized through fewer unemployed experiencing very long unemployment spells. Finally, there also seems a high level of suspicion of employers towards unemployed with a spell of more than twelve months (the so called “long term unemployed”). Employers seem to take the long spell as a signal for low employability and are not willing to take the risk (AMOSA 2006).

In a first estimation, additional group dummies are added to the model; one for each group. Because the group dummies are included simultaneously, each group coefficient shows the influence of that particular group membership while holding the other included memberships constant. To predict the effect of a multiple group membership in this estimation one would simple add the coefficients of the relevant groups (for woman and foreigner for example, to predict the overall effect for female foreigners). This simple approach does not allow for more complex interactions between the groups but restrains the estimation of the effect of the group memberships to simple linear additions. It does however give a good indication if the foreigner coefficient is truly driven through the fact that a person is foreign, rather than being young or male (foreigner unemployed are on average younger than Swiss unemployed and more often male). In a second step, interaction terms between the group of foreigners and the other group memberships are added. These are dummy variables which switch to 1 if both group memberships are given. The coefficient indicates how much the interview probability is increased or decreased if one is member of both groups (additional to the effect both group memberships have separately).

The results in Table 9 show that the foreigner coefficient is extremely stable when the other group variables are added. This shows that the high positive foreigner coefficient is not due to a correlation to another group variable (at least not to one which has been tested here). In terms of the other group coefficients, it's interesting to see that women show a much higher interview probability than men (the coefficient is large at +0.0094, however not statistically significant) when productivity related measures, application behaviour and occupational distribution are controlled for. In fact this finding is just as surprising as the overall positive coefficient for foreigners. This shows that the fact that women experience lower salaries (2008 men earned 24 % more (BFS 2008)) does not translate directly into a worse performance as an unemployed job seeker. Both younger and older job seekers have lower chances than the middle age category (unemployed 31 to 49 years old); older job seekers have a large negative coefficient (-0.0214) which is statistically significant on a 5 %-level. Finally, as expected, the long term unemployed show a much lower interview probability as the unemployed with a duration less than a year (-0.0283, statistically significant on a 10 %-level).

The third column shows the large changes which take place when the interaction terms are introduced. From the simple group coefficients, only the foreigner coefficient stays stable. All other group coefficients have been largely affected by the inclusion of the new interaction terms. The coefficient for women has turned from positive (0.0094) to negative (-0.0046). This shows that it really matters for the gender specific differences if the woman is Swiss or of foreign origin. While Swiss women have a lower interview probability than Swiss men (as can be seen by the negative coefficient for women), foreign women have an advantage over foreign men (as can be seen by adding the coefficient for women and the strongly positive coefficient of the interaction term for foreign women). When the focus is put on foreigners, the results show that while male foreigners have a strong advantage over male Swiss (as can be seen by the coefficient for foreigners, 0.0239), female foreigners have an even larger advantage over female Swiss (as can be seen by adding the coefficient for foreigners and the interaction term for foreign women, 0.0239 + 0.0300 = 0.0539). Why this large difference exists between the genders regarding their foreigner coefficient is not clear. Maybe there is a larger demand in the jobs female foreigners do. This could theoretically be tested, by adding occupational dummies to the estimations - one thereby estimates the difference purely on intra-occupational grounds. However, the model with the occupational dummies is very highly specified (as it adds another 119 dummies to an already large model) and therefore not reliable with this number of unemployed.

Dependent variable: Interview Probability			
Mean	0.0431	0.0431	0.0431
Std. Dev.	0.2031	0.2031	0.2031
Foreigner	0.0257*	0.0258*	0.0239
	(0.0111)	(0.0112)	(0.0146)
Woman		0.0094	-0.0046
		(0.0081)	(0.0092)
30 years old and younger		-0.0058	0.0127
		(0.0100)	(0.0145)
50 years old and older		-0.0214*	-0.0099
		(0.0099)	(0.0116)
Long term unemployed		-0.0283+	-0.0346*
		(0.0157)	(0.0159)
Foreign woman			0.0300+
			(0.0179)
Foreign 30 years old and younger			-0.0349+
			(0.0208)
Foreign 50 years old and older			-0.0317+
			(0.0190)
Foreign long term unemployed			0.0083
			(0.0155)
Productivity related measures			
Match between unemployed person and open position	yes	yes	yes
Level of praise in work certificates	yes	yes	yes
Highest attained education and former function of unemployed person	yes	yes	yes
Knowledge of the German language	yes	yes	yes
Measurements of application behaviour			
Method of applying	yes	yes	yes
Placement	yes	yes	yes
Search intensity	yes	yes	yes
Measurements of occupational distribution			
Industry	yes	yes	yes
Number of unemployed in the occupation	yes	yes	yes
Duration (13 dummies, omitted: Month 1)	yes	yes	yes
Constant	0.0136	0.0134	0.0076
	(0.0281)	(0.0278)	(0.0284)
Sample			
Number of measurements	6637	6637	6637
Number of unemployed	467	467	467
Estimation			
R-squared	0.0533	0.0550	0.0571
F-value	3.4068	3.3637	3.3380

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The match between the unemployed person and open position is measured in five dimensions (occupation, education, knowledge of the German language, age and gender). Each dimension is measured through a set of dummies (usually requirement fulfilled; requirement not fulfilled; no requirement mentioned in the job advertisement). The level of praise in the work certificate is measured as a set of dummies representing the lowest level of praise in the last three work certificates. The highest attained education is measured through five dummies and the former function of the unemployed through three dummies (low skilled, professional, management). For both method of applying and placements two dummies are entered. The number of unemployed in the occupation (119 categories are differentiated) is measured as the total number in the region (the canton of Zurich). The 13 duration dummies are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.

Table 9: Interaction between origin, gender, age and unemployment spell duration

The coefficient for young people has also changed sign (from -0.0058 to 0.0127). Again, this means that the effect is very different for foreign and Swiss unemployed aged 30 years or less. While it's Swiss young people have an advantage over the middle age category (+0.0127), foreign young people have a disadvantage (-0.0222). Among Swiss, the unemployed aged 50 years or more has a moderate disadvantage (-0.0099), while among foreigners, the group has a large disadvantage (-0.0416).

Focussing on foreigners, it seems that the positive foreigner effect is purely determined through the middle age category (31 to 49 year olds). For this group, the overall positive foreigner coefficient is relevant: Foreigners of the middle age group have an interview probability which is 0.0239 higher than the one of Swiss unemployed in the same age group. Both younger and older foreigners however have a slight disadvantage against the Swiss unemployed (-0.011 for the younger and -0.0078 for the older group). Because these coefficients are not statistically significant the thesis that these differences are actually zero cannot be rejected.

Finally, the inclusion of the interaction terms made the coefficient for the group of the long term unemployed even larger. Swiss long term unemployed have therefore a very large disadvantage over their compatriots which are not (yet) long term unemployed (-0.0346). Among unemployed foreigners, the drop in the interview probability over time is not quite as large. The difference between foreign long term unemployed and foreign short term unemployed (that is, less than twelve months unemployed) is – 0.0263. Assessing the group of foreigners, both short term and long term unemployed have an advantage over the short and long term unemployed Swiss respectively. Among the short term unemployed, the difference is 0.0239. Among the long term unemployed, it is even larger at 0.0322. However, this last result is not fully conclusive when compared to the split results from Annex 8. These results, which stem from separate estimations for applications written between month 1 and 6 and applications written from month 7 onwards, show that the foreigner coefficient becomes smaller later on in the spell. All estimations however show that foreigners have a higher interview probability than Swiss.

7. Conclusion

Levels and measures of productivity often lie at the heart of the discrimination debate, but they are difficult to measure. A new dataset on unemployed job seekers and their 6,637 applications includes the quality of the match between the job seeker and the requirements mentioned in the job advertisement he or she is applying to. This allows approaching productivity from another angle which is very similar to the one employers have to use in their assessment if they want to invite an applicant to a job interview or not. First separately and later simultaneously, measures of application behaviour and the occupational distribution were also added to the estimations, to assess if these might explain some of the group differences.

Adding these control variables greatly increased the coefficient for the group of the foreign job seekers from a small coefficient (0.0014) to a much larger one (0.0257) which is statistically significant on a 5 %-level. It is really quite surprising that foreigners do not have a disadvantage over Swiss – without even adding productivity related measures or other control variables. It is even more surprising that by holding productivity related variables, application behaviour and occupational distribution constant foreigners have an advantage over Swiss job seekers. Why that is cannot be explained through the data. One possible reason for these above-average chances might be that a selection process takes place. If unemployed foreigners who perceive their own chances to find a job soon as low leave Switzerland and return to their country of origin (first generation immigrants), the average interview probability in the pool of foreign unemployed which stay in Switzerland would increase (the higher probability would have to be due to some characteristic or skill not included in the models used in this study, otherwise these would have been held constant). This would also explain why job seekers from neighbouring countries have a particularly large positive coefficient (of course, this is at least partly also due to the cultural familiarity of employers and such job seekers with each other). Another (part) explanation could be that on average, foreigners apply to jobs where more applicants are screened in the interview process. They would enjoy a high probability to be invited to a job interview but their overall chance to receive a job offer would not have been increased. This would explain why foreign unemployed have a higher interview probability than Swiss unemployed but that this does not actually translate into a shorter unemployment spell or a lower unemployment rate. When looking at the interview probability, there certainly seems to be different rules at play than those for other labour market outcomes like wages. Foreigners earn less than Swiss citizens, at least in low skilled jobs – and that's where most of the unemployed foreigners search for employment (in high skilled jobs, foreigners actually earn more than Swiss citizens, see BFS 2009).

This study has set out to estimate the discriminatory component of a particular labour market outcome, the probability to be invited to a job interview once the unemployed has sent an application off. It has been found that the advantage is actually reversed from the one would expect based on studies in other countries or from other labour market outcomes in Switzerland. It is certainly too early on basis of these preliminary results to speak of a discrimination of Swiss citizens - after all, the results only stem from one unemployment agency, and despite the very large number of job advertisements collected, the observational number is still quite low in some groups. Also, there are several other labour market outcomes on which foreigners fare far worse (wages, unemployment duration, unemployment rate). However, the size of the coefficient – and its statistical significance – are quite a clear indication that at least on this outcome, the dynamics around discrimination might be more complex than previously thought.

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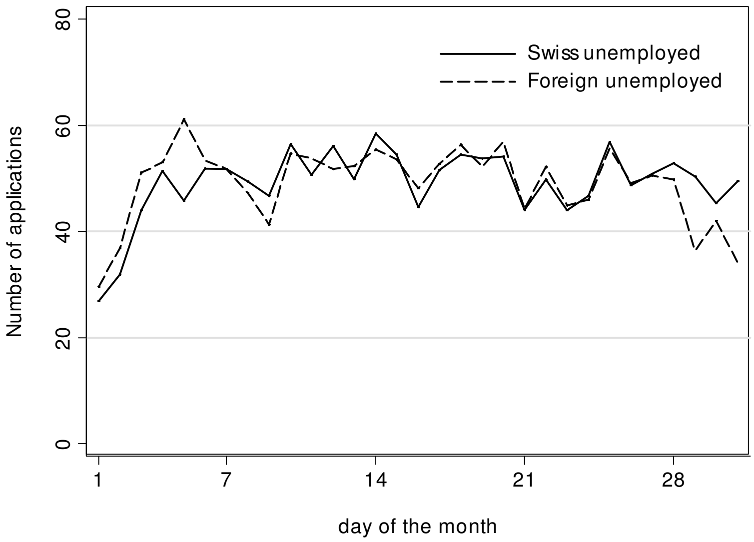
Annex

Annex 1: Applications recorded in a typical month at Zurich-Staffelstrasse



Note: Averages over the nine month of data collection are shown. Day 30 and day 31 were reweighed because their lower number of appearance. December was not taken into account. Weights are used to compensate for stratified sample.

Annex 2: Summary statistics

	All	Swiss	Foreigners
Interview Probability	0.0431	0.0455	0.0399
Matching quality			
Occupation match			
Occupation (5-Code) fulfilled	0.30	0.27	0.35
Occupation (3-Code) fulfilled	0.09	0.11	0.07
Occupation (1-Code) fulfilled	0.14	0.12	0.16
Requirement not fulfilled	0.46	0.49	0.42
No requirement mentioned	0.00	0.00	0.00
Education match			
Requirement (exactly) fulfilled	0.14	0.19	0.09
Underqualified	0.19	0.14	0.25
Overqualified	0.23	0.29	0.15
No requirement mentioned	0.44	0.38	0.51
German knowledge match			
Requirement fulfilled	0.24	0.35	0.10
Requirement not fulfilled	0.32	0.12	0.59
No requirement mentioned	0.44	0.53	0.31
Age match			
Requirement fulfilled	0.24	0.14	0.37
Too young	0.01	0.01	0.01
Too old	0.09	0.06	0.12
No requirement mentioned	0.66	0.78	0.49
Gender match			
Requirement fulfilled	0.16	0.15	0.17
Requirement not fulfilled	0.02	0.02	0.03
No requirement mentioned	0.82	0.84	0.79
Work Certificates (worst level out of the last three certificates)			
Below sufficient (3.9 and less out of 6 possible points)	0.12	0.09	0.16
Sufficient to good (4 to 4.9 out of 6 possible points)	0.19	0.19	0.19
Good to very good (5 to 6 out of 6 possible points)	0.53	0.61	0.43
No work certificate	0.16	0.11	0.23
Education			
No further education	0.36	0.17	0.62
Apprenticeship	0.28	0.37	0.16
Gymnasium	0.06	0.09	0.02
Technical college	0.10	0.15	0.04
University	0.10	0.10	0.11
Education not known	0.09	0.13	0.05
Former function			
Management	0.10	0.12	0.09
Professional	0.49	0.66	0.27
Low skilled	0.48	0.32	0.68
Knowledge of the German language			
Native German	0.55	0.82	0.18
High	0.02	0.00	0.04
Medium	0.03	0.01	0.04
Basic	0.15	0.04	0.29
Not tested	0.26	0.13	0.45
Application behaviour	0.72	0.78	0.64
Written application	0.24	0.20	0.30
Phone application	0.04	0.03	0.06
Personal application			
Public Placement (public employment service)	0.02	0.01	0.04
Private Placement (private recruiter)	0.05	0.05	0.05
Search intensity (number of application in the week the application was sent off)	4.12	4.08	4.19

Annex 2: Group characteristics (continued)

	All	Swiss	Foreigners
Industry			
No answer, first sector or “private household”	0.14	0.18	0.09
Industry	0.11	0.06	0.17
Building and Constructing	0.12	0.14	0.10
Trade and Commerce	0.18	0.09	0.31
Hospitality industry	0.04	0.04	0.03
Transport and Communication	0.06	0.06	0.04
Financial services	0.16	0.14	0.19
Business services (incl. IT)	0.04	0.07	0.01
Public administration	0.05	0.09	0.01
Health and social services	0.06	0.08	0.03
Other services	0.04	0.05	0.02
Number of unemployed in occupation in which the open position is placed	742.44	669.79	839.76
N (unemployed)	467	244	223
N (applications)	6637	3781	2,856

Annex 3: Interview probabilities controlled for productivity related measures (regional estimation)

Dependent variable: Interview Probability					
Mean	0.0431	0.0431	0.0431	0.0431	0.0431
Std. Dev.	0.2031	0.2031	0.2031	0.2031	0.2031
From a neighbouring country (Austria, France, Germany, Italy, Liechtenstein)	0.0436**	0.0425*	0.0421*	0.0310+	0.0288+
	(0.0166)	(0.0169)	(0.0165)	(0.0163)	(0.0167)
From an EU or EFTA country (other than the neighbouring countries)	-0.0072	0.0120	-0.0079	0.0005	0.0118
	(0.0177)	(0.0174)	(0.0190)	(0.0171)	(0.0184)
From an non-EU / non-EFTA country	-0.0114	0.0094	-0.0082	-0.0089	0.0049
	(0.0085)	(0.0108)	(0.0089)	(0.0105)	(0.0117)
Match between unemployed person and open position (occupation, education, German, age and gender match)	no	yes	yes	yes	yes
Level of praise in work certificates (the lowest level in one of the last 3 certificates determines the value)	no	no	yes	yes	yes
Highest attained education and former function of unemployed person	no	no	no	yes	yes
Duration (13 dummies, omitted: Month 1)	yes	yes	yes	yes	yes
Constant	0.0728**	0.0021	0.0540**	0.0573**	-0.0217
	(0.0124)	(0.0234)	(0.0141)	(0.0179)	(0.0271)
Sample					
Number of measurements	6637	6637	6637	6637	6637
Number of unemployed	467	467	467	467	467
Estimation					
R-squared	0.0141	0.0221	0.0154	0.0205	0.0287
F-value	3.0891	3.1613	2.7307	3.5115	3.1375

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The match between the unemployed person and open position is measured in five dimensions (occupation, education, knowledge of the German language, age and gender). Each dimension is measured through a set of dummies (usually requirement fulfilled; requirement not fulfilled; no requirement mentioned in the job advertisement). The level of praise in the work certificate is measured as a set of dummies representing the lowest level of praise in the last three work certificates. The highest attained education is measured through five dummies and the former function of the unemployed through three dummies (low skilled, professional, management). The 13 duration dummies are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.

Annex 4: Interview probabilities controlled for language knowledge (regional estimation)

Dependent variable: Interview Probability				
Mean	0.0431	0.0431	0.0431	0.0431
Std. Dev.	0.2031	0.2031	0.2031	0.2031
From a neighbouring country (Austria, France, Germany, Italy, Liechtenstein)	0.0288+	0.0288+	0.0297+	0.0297+
	(0.0164)	(0.0167)	(0.0167)	(0.0167)
From an EU or EFTA country (other than the neighbouring countries)	0.0026	0.0118	0.0278	0.0278
	(0.0181)	(0.0184)	(0.0189)	(0.0189)
From an non-EU / non-EFTA country	-0.0045	0.0049	0.0144	0.0147
	(0.0113)	(0.0117)	(0.0134)	(0.0134)
Match with German requirement mentioned in job advertisement				
Requirement fulfilled		0.0337**		0.0090
		(0.0112)		(0.0126)
No requirement mentioned		0.0146		-0.0019
		(0.0089)		(0.0092)
Knowledge of the German language (omitted category: native German)				
Basic			-0.0526**	-0.0486**
			(0.0162)	(0.0165)
Medium			0.0310	0.0344
			(0.0568)	(0.0584)
High			0.0113	0.0105
			(0.0198)	(0.0201)
Not tested			-0.0476**	-0.0437**
			(0.0136)	(0.0140)
Match between unemployed person and open position (occupation, education, age and gender **- without German match)**	yes	yes	yes	yes
Level of praise in work certificates (the lowest level in one of the last 3 certificates determines the value)	yes	yes	yes	yes
Highest attained education and former function of unemployed person	yes	yes	yes	yes
Duration (13 dummies, omitted: Month 1)	yes	yes	yes	yes
Constant	-0.0046	-0.0217	0.0330	0.0250
	(0.0262)	(0.0271)	(0.0259)	(0.0266)
Sample				
Number of measurements	6637	6637	6637	6637
Number of unemployed	467	467	467	467
Estimation				
R-squared	0.0264	0.0287	0.0341	0.0344
F-value	3.2032	3.1375	3.7165	3.5314

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The match between the unemployed person and open position is measured in five dimensions (occupation, education, knowledge of the German language, age and gender). Each dimension is measured through a set of dummies (usually requirement fulfilled; requirement not fulfilled; no requirement mentioned in the job advertisement). The level of praise in the work certificate is measured as a set of dummies representing the lowest level of praise in the last three work certificates. The highest attained education is measured through five dummies and the former function of the unemployed through three dummies (low skilled, professional, management). The 13 duration dummies are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.

Annex 5: Interview probabilities controlled for application behaviour (regional estimation)

Dependent variable: Interview Probability					
Mean	0.0431	0.0431	0.0431	0.0431	0.0431
Std. Dev.	0.2031	0.2031	0.2031	0.2031	0.2031
From a neighbouring country (Austria, France, Germany, Italy, Liechtenstein)	0.0436**	0.0396*	0.0433**	0.0433**	0.0391*
	(0.0166)	(0.0179)	(0.0166)	(0.0166)	(0.0178)
From an EU or EFTA country (other than the neighbouring countries)	-0.0072	-0.0070	-0.0080	-0.0074	-0.0077
	(0.0177)	(0.0173)	(0.0177)	(0.0175)	(0.0169)
From an non-EU / non-EFTA country	-0.0114	-0.0175*	-0.0120	-0.0116	-0.0181*
	(0.0085)	(0.0084)	(0.0085)	(0.0084)	(0.0083)
Method of applying (written, phone or personal application)	**no**	**yes**	**no**	**no**	**yes**
Placement (public or private)	**no**	**no**	**yes**	**no**	**yes**
Search intensity (number of applications written)	**no**	**no**	**no**	**yes**	**yes**
Duration (13 dummies, omitted: Month 1)	yes	yes	yes	yes	yes
Constant	0.0728**	0.0654**	0.0727**	0.0718**	0.0639**
	(0.0124)	(0.0124)	(0.0124)	(0.0122)	(0.0121)
Sample					
Number of measurements	6637	6637	6637	6637	6637
Number of unemployed	467	467	467	467	467
Estimation					
R-squared	0.0141	0.0294	0.0143	0.0142	0.0297
F-value	3.0891	3.5741	3.2468	3.0576	3.6350

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
For control for the method of applying and placements two dummies each are entered. The 13 duration dummies are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.

Annex 6: Interview probabilities controlled for occupational distribution (regional estimation)

Dependent variable: Interview Probability				
Mean	0.0431	0.0431	0.0431	0.0431
Std. Dev.	0.2031	0.2031	0.2031	0.2031
From a neighbouring country (Austria, France, Germany, Italy, Liechtenstein)	0.0436**	0.0519**	0.0499*	0.0438**
	(0.0166)	(0.0170)	(0.0198)	(0.0167)
From an EU or EFTA country (other than the neighbouring countries)	-0.0072	-0.0043	-0.0000	-0.0071
	(0.0177)	(0.0177)	(0.0271)	(0.0177)
From an non-EU / non-EFTA country	-0.0114	-0.0089	-0.0037	-0.0117
Industry (12 dummies)	**no**	**yes**	**no**	**no**
Occupation (119 dummies)	**no**	**no**	**yes**	**no**
Number of unemployed in the occupation	**no**	**no**	**no**	**yes**
Duration (13 dummies, omitted: Month 1)	yes	yes	yes	yes
Constant	0.0728**	0.0800**	0.0700**	0.0723**
	(0.0124)	(0.0169)	(0.0118)	(0.0132)
Sample				
Number of measurements	6637	6637	6637	6637
Number of unemployed	467	467	467	467
Estimation				
R-squared	0.0141	0.0180	0.0643	0.0141
F-value	3.0891	2.3717	2.1931	2.9185

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The number of unemployed in the occupation (119 categories are differentiated) is measured as the total number in the region (the canton of Zurich). The 13 duration dummies are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.

Annex 7: Interview probabilities controlled simultaneously for productivity related measures, application behaviour and occupational distribution (regional estimation)

Dependent variable: Interview Probability		
Mean	0.0431	0.0431
Std. Dev.	0.2031	0.2031
From a neighbouring country (Austria, France, Germany, Italy, Liechtenstein)	0.0436**	0.0350+
	(0.0166)	(0.0188)
From an EU or EFTA country (other than the neighbouring countries)	-0.0072	0.0257
	(0.0177)	(0.0175)
From an non-EU / non-EFTA country	-0.0114	0.0166
	(0.0085)	(0.0138)
Productivity related measures		
Match between unemployed person and open position	no	yes
Level of praise in work certificates	no	yes
Highest attained education and former function of unemployed person	no	yes
Knowledge of the German language	no	yes
Measurements of application behaviour		
Method of applying	no	yes
Placement	no	yes
Search intensity	no	yes
Measurements of occupational distribution		
Industry	no	yes
Number of unemployed in the occupation	no	yes
Duration (13 dummies, omitted: Month 1)	yes	yes
Constant	0.0728**	0.0157
	(0.0124)	(0.0288)
Sample		
Number of measurements	6637	6637
Number of unemployed	467	467
Estimation		
R-squared	0.0141	0.0537
F-value	3.0891	3.6507

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The match between the unemployed person and open position is measured in five dimensions (occupation, education, knowledge of the German language, age and gender). Each dimension is measured through a set of dummies (usually requirement fulfilled; requirement not fulfilled; no requirement mentioned in the job advertisement). The level of praise in the work certificate is measured as a set of dummies representing the lowest level of praise in the last three work certificates. The highest attained education is measured through five dummies and the former function of the unemployed through three dummies (low skilled, professional, management). For both method of applying and placements two dummies are entered. The number of unemployed in the occupation (119 categories are differentiated) is measured as the total number in the region (the canton of Zurich). The 13 duration dummies are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.

Annex 8: Estimation split according to duration period

Dependent variable: Interview Probability	All applications		First 6 months of unemployment		Month 7 and later	
Mean	0.0431	0.0431	0.0549	0.0549	0.0302	0.0302
Std. Dev.	0.2031	0.2031	0.2278	0.2278	0.1712	0.1712
Foreigner	0.0014	0.0257*	-0.0012	0.0330+	0.0048	0.0107
	(0.0082)	(0.0111)	(0.0129)	(0.0171)	(0.0093)	(0.0106)
Productivity related measures						
Match between unemployed person and open position)	no	yes	no	yes	no	yes
Level of praise in work certificates	no	yes	no	yes	no	yes
Highest attained education and former function of unemployed person	no	yes	no	yes	no	yes
Knowledge of the German language	no	yes	no	yes	no	yes
Measurements of application behaviour						
Method of applying (written, phone or personal application,	no	yes	no	yes	no	yes
Placement (public or private)	no	yes	no	yes	no	yes
Search intensity (number of applications written)	no	yes	no	yes	no	yes
Measurements of occupational distribution						
Industry (12 dummies)	no	yes	no	yes	no	yes
Number of unemployed in the occupation	no	yes	no	yes	no	yes
Duration (13 dummies, omitted: Month 1)	yes	yes	yes	yes	yes	yes
Constant	0.0768**	0.0136	0.0777**	-0.0100	0.0136	-0.0169
	(0.0124)	(0.0281)	(0.0124)	(0.0452)	(0.0130)	(0.0337)
Sample						
Number of measurements	6637	6637	3460	3460	3177	3177
Number of unemployed	467	467	323	323	219	219
Estimation						
R-squared	0.0092	0.0533	0.0038	0.052	0.0079	0.083
F-value	2.5938	3.4068	1.0343	3.4415	1.1238	5.3192

Notes: Robust standard errors in parentheses.
+, *, ** denote significance at the 10 %, 5 % and 1 % level.
The match between the unemployed person and open position is measured in five dimensions (occupation, education, knowledge of the German language, age and gender). Each dimension is measured through a set of dummies (usually requirement fulfilled; requirement not fulfilled; no requirement mentioned in the job advertisement). The level of praise in the work certificate is measured as a set of dummies representing the lowest level of praise in the last three work certificates. The highest attained education is measured through five dummies and the former function of the unemployed through three dummies (low skilled, professional, management). For both method of applying and placements two dummies are entered. The number of unemployed in the occupation (119 categories are differentiated) is measured as the total number in the region (the canton of Zurich). The 13 duration dummies are: 1 (omitted), 2, 3, 4, 5-6, 7-8, 9-10, 11-12, 13-15, 16-18, 19-21, 22-24, 25 and more months.